BBVA | RESEARCH

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

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

Maximo Camacho[a] and Jaime Martinez-Martin[b]

June 2012

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.

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) $\qquad Y^*_{III} = Y_{09} + Y_{08} + Y_{07}$

or equivalently

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

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

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

(4) $\qquad lnY^*_{III} = ln3 + \dfrac{1}{3}(lnY_{09} + lnY_{08} + lnY_{07})$

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

(5) $\qquad \begin{aligned} lnY^*_{III} - lnY^*_{II} &= \dfrac{1}{3}(lnY_{09} + lnY_{08} + lnY_{07}) - \dfrac{1}{3}(lnY_{06} + lnY_{05} + lnY_{04}) = \\ &= \dfrac{1}{3}[(lnY_{09} - lnY_{06}) + (lnY_{08} - lnY_{05}) + (lnY_{07} - lnY_{04})] \end{aligned}$

and by redefining these terms as $y^*_{III} = lnY^*_{III} - lnY^*_{II}$, and $y_j = lnY_j - lnY_{j-1}$, one can define

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

This expression can directly be generalized as

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

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) $\qquad x_t = \rho_1 x_{t-1} + ... + \rho_{p1} x_{t-p1} = e_t$

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

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

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

(11) $\qquad z_t^i = \boldsymbol{\beta}_i x_t + u_t^i$

(12) $\qquad u_t^i = d_1^i u_{t\text{-}q}^i + ... + d_{p3}^i u_{t\text{-}p3}^i + \boldsymbol{\varepsilon}_t^i$

where $\varepsilon_t^i \sim iN(O, \sigma_i^2)$. 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) $\qquad y_t^* = \boldsymbol{\beta}_y \left(\dfrac{1}{3} x_t + \dfrac{2}{3} x_{t\text{-}1} + x_{t\text{-}2} + \dfrac{2}{3} x_{t\text{-}3} + \dfrac{1}{3} x_{t\text{-}4} \right) + \left(\dfrac{1}{3} u_t^y + \dfrac{2}{3} u_{t\text{-}1}^y + u_{t\text{-}2}^y + \dfrac{2}{3} u_{t\text{-}3}^y + \dfrac{1}{3} u_{t\text{-}4}^y \right)$

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) $\qquad Z_{it}^* = \boldsymbol{\beta}_i x_{t\text{-}j} + u_t^i$

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) $\qquad Z_{ft}^* = \boldsymbol{\beta}_f x_{t+h} + u_t^f$

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 $\partial_t \sim N(O, \sigma_\partial^2)$ 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
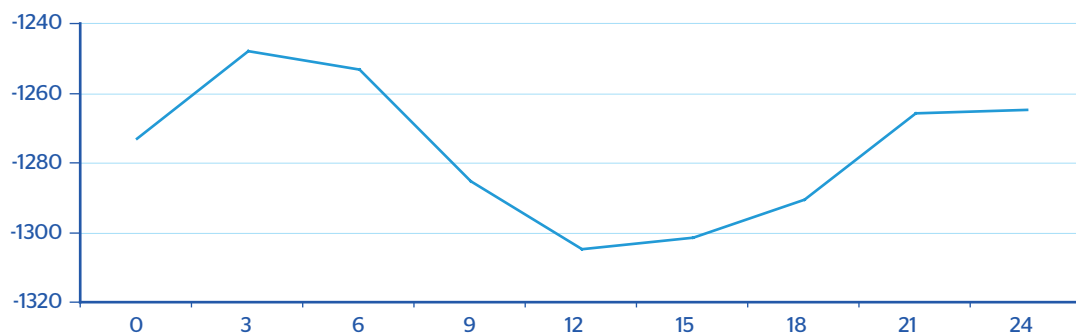
Notes. The term spread at time *t* has been related to the common factor at time *t+h*. In this figure, *h* appears in the horizontal axis and the log likelihoods reached by the dynamic factor model appear in the vertical axis.
Source: BBVA Research

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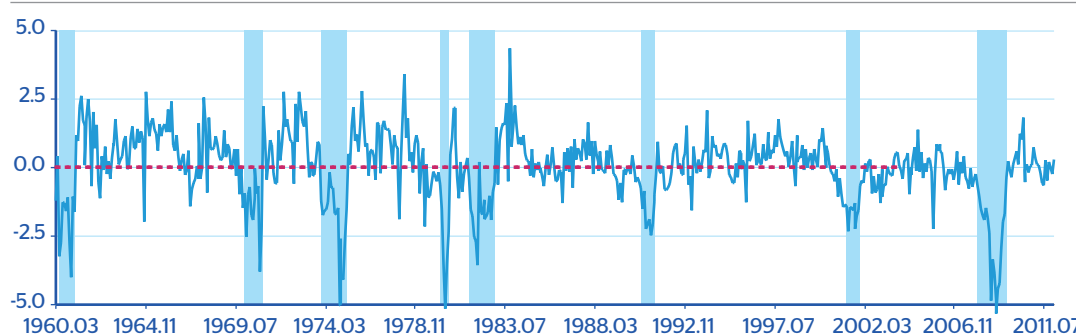
Notes: Shaded areas correspond to recessions as documented by the NBER.
Source: BBVA Research

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:

$$(16) \qquad X_t = C_{s_t} + \sum_{j=1}^{p} \alpha_j X_{t-j} + \varepsilon_t \; ,$$

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 $\varepsilon_t \sim iidN(0, \sigma)$ [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) $\qquad p(s_t=i/s_{t-1}=j, s_{t-2}=h,..., X_{t-1}) = p(s_t=i/s_{t-1}=j)=p_{ij}$.

Taking the maximum likelihood estimates of parameters, reported in Table 3, in the regime represented by $s_t=0$, the 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	-1.99	0.88	0.98	0.91
(0.04)	(0.11)	(0.05)	(0.01)	(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, $\varepsilon_t \sim iidN(0, \sigma)$, 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
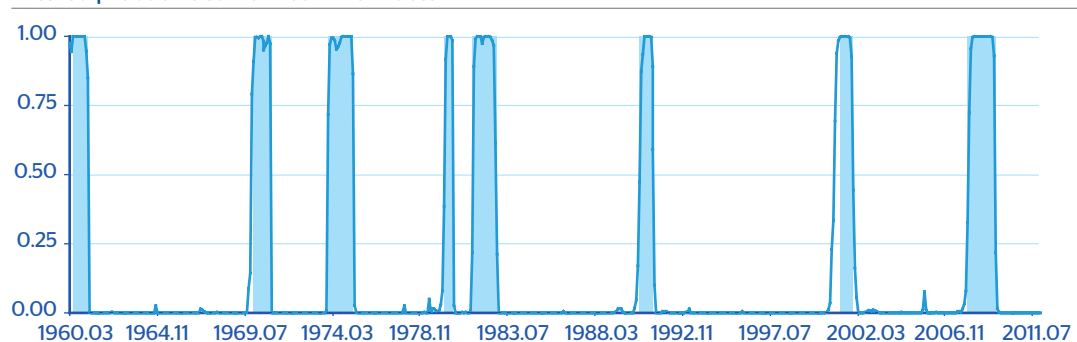
Notes: Shaded areas correspond to recessions as documented by the NBER.
Source: BBVA Research

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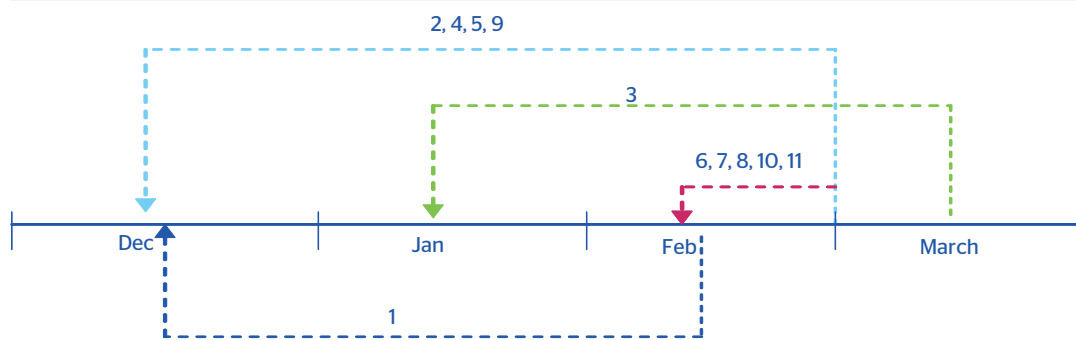
Notes: Number correspond to indicators as Table 1 summarizes.
Source: BBVA Research

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

Backcasts
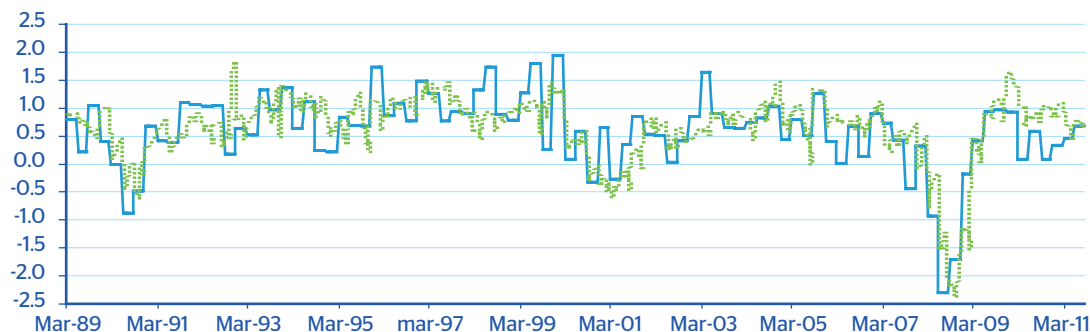
Nowcasts
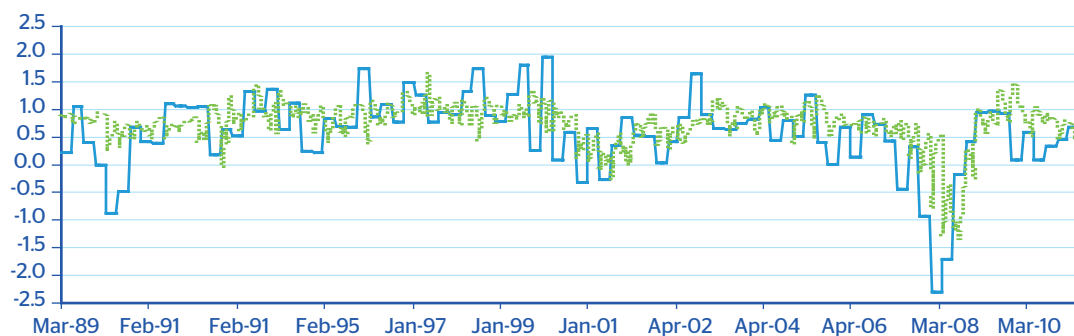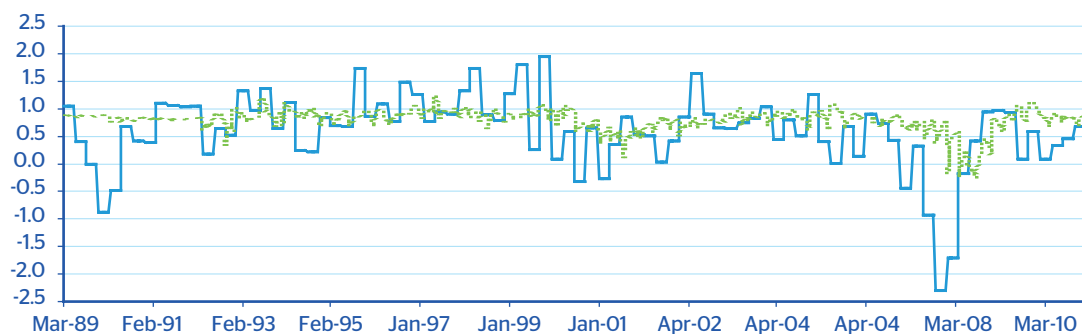
Forecasts

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

$$
\text{(A1)} \quad
\begin{bmatrix} y_t^* \\ Z_{it}^* \\ Z_{ft}^* \end{bmatrix}
=
\begin{bmatrix}
O & \dfrac{\beta_y}{3} & \dfrac{2\beta_y}{3} & \beta_y & \dfrac{2\beta_y}{3} & \dfrac{\beta_y}{3} & \dfrac{1}{3} & \dfrac{2}{3} & 1 & \dfrac{2}{3} & \dfrac{1}{3} & O & O \\
O & \beta_i & O & \ldots & O & O & O & O & O & O & O & 1 & O \\
\beta_f & \beta_f & & & O & O & O & O & O & O & O & O & 1
\end{bmatrix}
\begin{bmatrix} x_{t+1} \\ x_t \\ \vdots \\ x_{t-4} \\ u_t^y \\ \vdots \\ u_{t-4}^y \\ u_t^i \\ u_t^f \end{bmatrix}
$$

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

$$
\text{(A2)} \quad
\begin{bmatrix} x_{t+1} \\ x_t \\ \vdots \\ x_{t-4} \\ u_t^y \\ \vdots \\ u_{t-4}^y \\ u_t^i \\ u_t^f \end{bmatrix}
=
\begin{bmatrix}
\rho_1 & \ldots & O & O & O & \ldots & & O \\
1 & & O & & \ldots & & & O \\
\vdots & \ddots & \vdots & & \ldots & & & \vdots \\
O & \ldots & 1 & O & & \ldots & & O \\
O & \ldots & & O & d_1^y & O & O & O \\
\vdots & \ldots & & & \ldots & \ddots & & \vdots \\
O & \ldots & & & 1 & O & & O \\
O & \ldots & & & O & O & d_1^i & O \\
O & \ldots & & & O & O & O & d_1^f
\end{bmatrix}
\begin{bmatrix} x_t \\ x_{t-1} \\ \vdots \\ x_{t-5} \\ u_{t-1}^y \\ \vdots \\ u_{t-5}^y \\ u_{t-1}^i \\ u_{t-1}^f \end{bmatrix}
+
\begin{bmatrix} e_{t+1} \\ e_t \\ \vdots \\ e_{t-5} \\ \varepsilon_{t-1}^y \\ \vdots \\ \varepsilon_{t-5}^y \\ \varepsilon_t^i \\ \varepsilon_t^f \end{bmatrix}
$$

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

References

Aruoba, B., and Diebold, F. 2010. Real-time macroeconomic monitoring: Real activity, inflation, and interactions. *American Economic Review: Papers and Proceedings* 100: 20-24.

Berge, T., and Jorda, O. 2011. The classification of economic activity into expansions and recessions. *American Economic Journal; Macroeconomics* 3: 246-77.

Camacho, M. Perez Quiros, G., and Poncela, P. 2012. Extracting nonlinear signals from several economic indicators. CEPR Working Paper No. 8865.

Camacho, M. and R. Doménech. 2012. MICA-BBVA: A factor model of economic and financial indicators for short-term GDP forecasting. *SERIES: Journal of the Spanish Economic Association.* Forthcoming.

Camacho, M., and Perez Quiros, G. 2007. Jump-and-rest effect of U.S. business cycles. *Studies in Nonlinear Dynamics and Econometrics* 11(4): article 3

Camacho, M., and Perez Quiros, G. 2010. Introducing the Euro-STING: Short Term INdicator of euro area Growth. *Journal of Applied Econometrics* 25: 663-694.

Diebold F., and Mariano, R. 1995. Comparing predictive accuracy. *Journal of Business and Economic Statistics* 13: 253-263.

Giacomini, R., and Rossi, B. 2010. Forecast comparisons in unstable environments. *Journal of Applied Econometric*s 25: 595-620.

Giannone, D., Reichlin, L., and Small, D. 2008. Nowcasting: The real-time informational content of macroeconomic data. *Journal of Monetary Economics* 55: 665-676.

Harvey, D., Leybourne, S., and Newbold, P. 1997. Testing equality of prediction mean squared errors. *International Journal of Forecasting* 13: 287-291.

Mariano, R., and Murasawa, Y. 2003. A new coincident index of business cycles based on monthly and quarterly series. *Journal of Applied Econometrics* 18: 427-443.

Stark, T. and D. Croushore (2002). Forecasting with Real-Time Data Set for Macroeconomists. *Journal of Macroeconomics* 24: 507-531.

Stock, J., and Watson, M. 1991. A probability model of the coincident economic indicators. In Kajal Lahiri and Geoffrey Moore editors, *Leading economic indicators, new approaches and forecasting records.* Cambridge University Press, Cambridge.

Wheelock D., and Wohar, M. 2009. Can the term spread predict output growth and recessions? A survey of the literature. *Federal Reserve Bank of St. Louis Review* 91: 419-440.

Working Papers

09/01 **K.C. Fung, Alicia García-Herrero and Alan Siu:** Production Sharing in Latin America and East Asia.

09/02 **Alicia García-Herrero, Jacob Gyntelberg and Andrea Tesei:** The Asian crisis: what did local stock markets expect?

09/03 **Alicia García-Herrero and Santiago Fernández de Lis:** The Spanish Approach: Dynamic Provisioning and other Tools.

09/04 **Tatiana Alonso:** Potencial futuro de la oferta mundial de petróleo: un análisis de las principales fuentes de incertidumbre.

09/05 **Tatiana Alonso:** Main sources of uncertainty in formulating potential growth scenarios for oil supply.

09/06 **Ángel de la Fuente y Rafael Doménech:** Convergencia real y envejecimiento: retos y propuestas.

09/07 **KC FUNG, Alicia García-Herrero and Alan Siu:** Developing Countries and the World Trade Organization: A Foreign Influence Approach.

09/08 **Alicia García-Herrero, Philip Woolbridge and Doo Yong Yang:** Why don't Asians invest in Asia? The determinants of cross-border portfolio holdings.

09/09 **Alicia García-Herrero, Sergio Gavilá and Daniel Santabárbara:** What explains the low profitability of Chinese Banks?

09/10 **J.E. Boscá, R. Doménech and J. Ferri: Tax Reforms and Labour-market Performance:** An Evaluation for Spain using REMS.

09/11 R. **Doménech and Angel Melguizo:** Projecting Pension Expenditures in Spain: On Uncertainty, Communication and Transparency.

09/12 **J.E. Boscá, R. Doménech and J. Ferri:** Search, Nash Bargaining and Rule of Thumb Consumers.

09/13 **Angel Melguizo, Angel Muñoz, David Tuesta y Joaquín Vial:** Reforma de las pensiones y política fiscal: algunas lecciones de Chile.

09/14 **Máximo Camacho: MICA-BBVA:** A factor model of economic and financial indicators for short-term GDP forecasting.

09/15 **Angel Melguizo, Angel Muñoz, David Tuesta and Joaquín Vial:** Pension reform and fiscal policy: some lessons from Chile.

09/16 **Alicia García-Herrero and Tuuli Koivu:** China's Exchange Rate Policy and Asian Trade.

09/17 **Alicia García-Herrero, K.C. Fung and Francis Ng:** Foreign Direct Investment in Cross-Border Infrastructure Projects.

09/18 **Alicia García Herrero y Daniel Santabárbara García:** Una valoración de la reforma del sistema bancario de China.

09/19 **C. Fung, Alicia García-Herrero and Alan Siu:** A Comparative Empirical Examination of Outward Direct Investment from Four Asian Economies: China, Japan, Republic of Korea and Taiwan.

09/20 **Javier Alonso, Jasmina Bjeletic, Carlos Herrera, Soledad Hormazábal, Ivonne Ordóñez, Carolina Romero y David Tuesta:** Un balance de la inversión de los fondos de pensiones en infraestructura: la experiencia en Latinoamérica.

09/21 **Javier Alonso, Jasmina Bjeletic, Carlos Herrera, Soledad Hormazábal, Ivonne Ordóñez, Carolina Romero y David Tuesta:** Proyecciones del impacto de los fondos de pensiones en la inversión en infraestructura y el crecimiento en Latinoamérica.

10/01 **Carlos Herrera:** Rentabilidad de largo plazo y tasas de reemplazo en el Sistema de Pensiones de México.

10/02 **Javier Alonso, Jasmina Bjeletic, Carlos Herrera, Soledad Hormazabal, Ivonne Ordóñez, Carolina Romero, David Tuesta and Alfonso Ugarte:** Projections of the Impact of Pension Funds on Investment in Infrastructure and Growth in Latin America.

10/03 **Javier Alonso, Jasmina Bjeletic, Carlos Herrera, Soledad Hormazabal, Ivonne Ordóñez, Carolina Romero, David Tuesta and Alfonso Ugarte:** A balance of Pension Fund Infrastructure Investments: The Experience in Latin America.

10/04 **Mónica Correa-López y Ana Cristina Mingorance-Arnáiz:** Demografía, Mercado de Trabajo y Tecnología: el Patrón de Crecimiento de Cataluña, 1978-2018.

10/05 **Soledad Hormazabal D.:** Gobierno Corporativo y Administradoras de Fondos de Pensiones (AFP). El caso chileno.

10/06 **Soledad Hormazabal D.:** Corporate Governance and Pension Fund Administrators: The Chilean Case.

10/07 **Rafael Doménech y Juan Ramón García:** ¿Cómo Conseguir que Crezcan la Productividad y el Empleo, y Disminuya el Desequilibrio Exterior?

10/08 **Markus Brückner and Antonio Ciccone:** International Commodity Prices, Growth, and the Outbreak of Civil War in Sub-Saharan Africa.

10/09 **Antonio Ciccone and Marek Jarocinski:** Determinants of Economic Growth: Will Data Tell?

10/10 **Antonio Ciccone and Markus Brückner:** Rain and the Democratic Window of Opportunity.

10/11 **Eduardo Fuentes:** Incentivando la cotización voluntaria de los trabajadores independientes a los fondos de pensiones: una aproximación a partir del caso de Chile.

10/12 **Eduardo Fuentes:** Creating incentives for voluntary contributions to pension funds by independent workers: A primer based on the case of Chile.

10/13 **J. Andrés, J.E. Boscá, R. Doménech and J. Ferri:** Job Creation in Spain: Productivity Growth, Labour Market Reforms or both.

10/14 **Alicia García-Herrero:** Dynamic Provisioning: Some lessons from existing experiences.

10/15 **Arnoldo López Marmolejo and Fabrizio López-Gallo Dey:** Public and Private Liquidity Providers.

10/16 **Soledad Zignago:** Determinantes del comercio internacional en tiempos de crisis.

10/17 **Angel de la Fuente and José Emilio Boscá:** EU cohesion aid to Spain: a data set Part I: 2000-06 planning period.

10/18 **Angel de la Fuente:** Infrastructures and productivity: an updated survey.

10/19 **Jasmina Bjeletic, Carlos Herrera, David Tuesta y Javier Alonso:** Simulaciones de rentabilidades en la industria de pensiones privadas en el Perú.

10/20 **Jasmina Bjeletic, Carlos Herrera, David Tuesta and Javier Alonso:** Return Simulations in the Private Pensions Industry in Peru.

10/21 **Máximo Camacho and Rafael Doménech:** MICA-BBVA: A Factor Model of Economic and Financial Indicators for Short-term GDP Forecasting.

10/22 **Enestor Dos Santos and Soledad Zignago:** The impact of the emergence of China on Brazilian international trade.

10/23 **Javier Alonso, Jasmina Bjeletic y David Tuesta:** Elementos que justifican una comisión por saldo administrado en la industria de pensiones privadas en el Perú.

10/24 **Javier Alonso, Jasmina Bjeletic y David Tuesta:** Reasons to justify fees on assets in the Peruvian private pension sector.

10/25 **Mónica Correa-López, Agustín García Serrador and Cristina Mingorance-Arnáiz:** Product Market Competition and Inflation Dynamics: Evidence from a Panel of OECD Countries.

10/26 **Carlos A. Herrera:** Long-term returns and replacement rates in Mexico's pension system.

10/27 **Soledad Hormazábal:** Multifondos en el Sistema de Pensiones en Chile.

10/28 **Soledad Hormazábal:** Multi-funds in the Chilean Pension System.

10/29 **Javier Alonso, Carlos Herrera, María Claudia Llanes y David Tuesta:** Simulations of long-term returns and replacement rates in the Colombian pension system.

10/30 **Javier Alonso, Carlos Herrera, María Claudia Llanes y David Tuesta:** Simulaciones de rentabilidades de largo plazo y tasas de reemplazo en el sistema de pensiones de Colombia.

11/01 **Alicia García Herrero:** Hong Kong as international banking center: present and future.

11/02 **Arnoldo López-Marmolejo:** Effects of a Free Trade Agreement on the Exchange Rate Pass-Through to Import Prices.

11/03 **Angel de la Fuente:** Human capital and productivity

11/04 **Adolfo Albo y Juan Luis Ordaz Díaz:** Los determinantes de la migración y factores de la expulsión de la migración mexicana hacia el exterior, evidencia municipal.

11/05 **Adolfo Albo y Juan Luis Ordaz Díaz:** La Migración Mexicana hacia los Estados Unidos: Una breve radiografía.

11/06 **Adolfo Albo y Juan Luis Ordaz Díaz:** El Impacto de las Redes Sociales en los Ingresos de los Mexicanos en EEUU.

11/07 **María Abascal, Luis Carranza, Mayte Ledo y Arnoldo López Marmolejo:** Impacto de la Regulación Financiera sobre Países Emergentes.

11/08 **María Abascal, Luis Carranza, Mayte Ledo and Arnoldo López Marmolejo:** Impact of Financial Regulation on Emerging Countries.

11/09 **Angel de la Fuente y Rafael Doménech:** El impacto sobre el gasto de la reforma de las pensiones: una primera estimación.

11/10 **Juan Yermo:** El papel ineludible de las pensiones privadas en los sistemas de ingresos de jubilación.

11/11 **Juan Yermo:** The unavoidable role of private pensions in retirement income systems.

11/12 **Angel de la Fuente and Rafael Doménech:** The impact of Spanish pension reform on expenditure: A quick estimate.

11/13 **Jaime Martínez-Martín:** General Equilibrium Long-Run Determinants for Spanish FDI: A Spatial Panel Data Approach.

11/14 **David Tuesta:** Una revisión de los sistemas de pensiones en Latinoamérica.

11/15 **David Tuesta:** A review of the pension systems in Latin America.

11/16 **Adolfo Albo y Juan Luis Ordaz Díaz:** La Migración en Arizona y los efectos de la Nueva Ley "SB-1070".

11/17 **Adolfo Albo y Juan Luis Ordaz Díaz:** Los efectos económicos de la Migración en el país de destino. Los beneficios de la migración mexicana para Estados Unidos.

11/18 **Angel de la Fuente:** A simple model of aggregate pension expenditure.

11/19 **Angel de la Fuente y José E. Boscá:** Gasto educativo por regiones y niveles en 2005.

11/20 **Máximo Camacho and Agustín García Serrador:** The Euro-Sting revisited: PMI versus ESI to obtain euro area GDP forecasts.

11/21 **Eduardo Fuentes Corripio:** Longevity Risk in Latin America.

11/22 **Eduardo Fuentes Corripio:** El riesgo de longevidad en Latinoamérica.

11/23 **Javier Alonso, Rafael Doménech y David Tuesta:** Sistemas Públicos de Pensiones y la Crisis Fiscal en la Zona Euro. Enseñanzas para América Latina.

11/24 **Javier Alonso, Rafael Doménech y David Tuesta:** Public Pension Systems and the Fiscal Crisis in the Euro Zone. Lessons for Latin America.

11/25 **Adolfo Albo y Juan Luis Ordaz Díaz:** Migración mexicana altamente calificadaen EEUU y Transferencia de México a Estados Unidos a través del gasto en la educación de los migrantes.

11/26 **Adolfo Albo y Juan Luis Ordaz Díaz:** Highly qualified Mexican immigrants in the U.S. and transfer of resources to the U.S. through the education costs of Mexican migrants.

11/27 **Adolfo Albo y Juan Luis Ordaz Díaz:** Migración y Cambio Climático. El caso mexicano.

11/28 **Adolfo Albo y Juan Luis Ordaz Díaz:** Migration and Climate Change: The Mexican Case.

11/29 **Ángel de la Fuente y María Gundín:** Indicadores de desempeño educativo regional: metodología y resultados para los cursos 2005-06 a 2007-08.

11/30 **Juan Ramón García** Desempleo juvenil en España: causas y soluciones.

11/31 **Juan Ramón García:** Youth unemployment in Spain: causes and solutions.

11/32 **Mónica Correa-López and Beatriz de Blas:** International transmission of medium-term technology cycles: Evidence from Spain as a recipient country.

11/33 **Javier Alonso, Miguel Angel Caballero, Li Hui, María Claudia Llanes, David Tuesta, Yuwei Hu and Yun Cao:** Potential outcomes of private pension developments in China.

11/34 **Javier Alonso, Miguel Angel Caballero, Li Hui, María Claudia Llanes, David Tuesta, Yuwei Hu and Yun Cao:** Posibles consecuencias de la evolución de las pensiones privadas en China.

11/35 **Enestor Dos Santos:** Brazil on the global finance map: an analysis of the development of the Brazilian capital market

11/36 **Enestor Dos Santos, Diego Torres y David Tuesta:** Una revisión de los avances en la inversión en infraestructura en Latinoamerica y el papel de los fondos de pensiones privados.

11/37 **Enestor Dos Santos, Diego Torres and David Tuesta:** A review of recent infrastructure investment in Latin America and the role of private pension funds.

11/ 38 **Zhigang Li and Minqin Wu:** Estimating the Incidences of the Recent Pension Reform in China: Evidence from 100,000 Manufacturers.

12/01 **Marcos Dal Bianco, Máximo Camacho andGabriel Pérez-Quiros:** Short-run forecasting of the euro-dollar exchange rate with economic fundamentals.

12/02 **Guoying Deng, Zhigang Li and Guangliang Ye:** Mortgage Rate and the Choice of Mortgage Length: Quasi-experimental Evidence from Chinese Transaction-level Data.

12/03 **George Chouliarakis and Mónica Correa-López:** A Fair Wage Model of Unemployment with Inertia in Fairness Perceptions.

2/04 **Nathalie Aminian, K.C. Fung, Alicia García-Herrero, Francis NG:** Trade in services: East Asian and Latin American Experiences.

12/05 **Javier Alonso, Miguel Angel Caballero, Li Hui, María Claudia Llanes, David Tuesta, Yuwei Hu and Yun Cao:** Potential outcomes of private pension developments in China (Chinese Version).

12/06 **Alicia Garcia-Herrero, Yingyi Tsai and Xia Le:** RMB Internationalization: What is in for Taiwan?

12/07 **K.C. Fung, Alicia Garcia-Herrero, Mario Nigrinis Ospina:** Latin American Commodity Export Concentration: Is There a China Effect?

12/08 **Matt Ferchen, Alicia Garcia-Herrero and Mario Nigrinis:** Evaluating Latin America's Commodity Dependence on China.

12/09 **Zhigang Li, Xiaohua Yu, Yinchu Zeng and Rainer Holst:** Estimating transport costs and trade barriers in China: Direct evidence from Chinese agricultural traders.

12/10 **Maximo Camacho and Jaime Martinez-Martin:** Real-time forecasting US GDP from small-scale factor models.

BBVA Research's publications can be viewed on the following website: http://www.bbvaresearch.com