US real-time macroeconomic monitoring from small-scale factor models*

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Abstract

This paper proposes two refinements to the baseline method of monitoring developed by Aruoba and Diebold (2010). First, we adapt the model to include soft and leading indicators such as financial time series. Second, we examine the predictive performance of the model when the goal is to forecast real GDP. Our main findings reveal that enlarging the baseline model does not lead to any distortion in computing the business cycle coincident indicator. However, soft indicators lead to substantial improvements in the ability of the model to capture the US business cycle dynamics …(To be completed)

Key words: real-time forecasting, US GDP, business cycles

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1. Introduction

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

In the context of the US economy, Auroba and Diebold (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 the 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 with the different starting and ending dates of the indicators, as is 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 cohere strongly with the NBER chronology, plunging down 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? To examine this question, the baseline model is extended to include leading along with coincident indicators. Second, can the model be used to produce accurate forecasts of real GDP growth? To develop this analysis, the predictive model is estimated in a way to take into account that the goal is to compute short-term forecast of real GDP. 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 the real-time data flow. In addition, according to the standard literature on forecasting, the forecasts are carried out in a recursive way and with every new vintage, as the model is re-estimated and the forecasts for different horizons are computed.

Our main results can be summarized as follows. Enlarging the baseline model does not lead to any distortion in computing the business cycle coincident indicator. However, soft indicators lead to substantial improvements in the accuracy of short-run real GDP forecasts. Notably, the forecast improvements do not appear when financial indicators are included in the model. This result agrees with Wheelock and Wohar (2009), who find that the term spread to forecast output growth has diminished in recent years.

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

$$Y_{III}^* = Y_{09} + Y_{08} + Y_{07}\,, \tag{1}$$

or equivalently

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

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

$$Y_{III}^* = 3\left(Y_{09} + Y_{08} + Y_{07}\right)^{1/3}, \tag{3}$$

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

$$\ln Y_{III}^* = \ln 3 + \frac{1}{3}\left(\ln Y_{09} + \ln Y_{08} + \ln Y_{07}\right), \tag{4}$$

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

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

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

$$y_{III}^{*} = \frac{1}{3} y_{09} + \frac{2}{3} y_{08} + y_{07} + \frac{2}{3} y_{06} + \frac{1}{3} y_{05}. \tag{6}$$

This expression can directly be generalized as

$$y_t^{*} = \frac{1}{3} y_t + \frac{2}{3} y_{t-1} + y_{t-2} + \frac{2}{3} y_{t-3} + \frac{1}{3} y_{t-4}. \tag{7}$$

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 variables introduced 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

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

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

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*)

$$y_t = \beta_y x_t + u_t^y, \tag{9}$$

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

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

$$z_t^i = \beta_i x_t + u_t^i, \tag{11}$$

$$u_t^i = d_1^i u_{t-q}^i + \ldots + d_{p3}^i u_{t-p3}^i + \varepsilon_t^i, \tag{12}$$

where $\varepsilon_t^i \sim iN\left(0, \sigma_i^2\right)$. 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

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

The unit roots of hard indicators are accounted for by using the series in their monthly growth rates. Soft indicators are used in levels. Calling Z_i^* the monthly growth rates of hard or the level of soft variables, the dynamics of these variables relationship are captured by

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

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

Finally, following the suggestions of Wheelock and Wohar (2009), financial indicators are treated as leading indicators of the current business conditions. Accordingly, 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, which represents the overall state of the economy, as follows:

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

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 data do not contain missing data which were clearly an unrealistic assumption since our data exhibits ragged ends and mixing frequencies problems. Fortunately, Mariano and Murasawa (2003) show that the Kalman filter can be used to estimate model's parameters and to infer unobserved components and missing observations. These authors propose replacing the missing observations with random draws ϑ_t, whose distribution cannot depend on the parameter space that characterizes the Kalman filter.[1] Hence, although this procedure leaves the matrices used in the Kalman filter conformable, the rows containing missing observations

[1] We assume that $\vartheta_t \sim N\left(0, \sigma_\vartheta^2\right)$ for convenience but replacements by constants would also be valid.

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.

3. Empirical results

3.1. Preliminary analysis of data

The data set managed in this paper spans the period from January 1960 to June 2011.[2] 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. Second, for a given quarter they should refer to data of this quarter published before the figure of GDP 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 at least in one third of the sample.

Shortlisted indicators at an early stage are characterized by a strong link with the GDP cycle, starting from the set of coincident economic indicators used in Aruoba and Diebold (2010), quarterly real GDP, and monthly industrial production, payroll employment, real personal income less transfers, and trade sales. The 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 does not exhibit publication delays. Among the hard indicators, we include industrial new orders, housing starts and SP500. Among the soft indicators, we include consumer confident and manufacturing PMI. Finally, the set of indicators is enlarged by including the term spread, which is measured as the difference between the yields on long-term and short-term maturities (10-yar Treasury bond yield at constant maturity minus Federal Funds effective rate). Financial variables are available on a timely basis.

As a result of these criteria along with above required properties, the indicators finally included in our model and their respective release lag-time are listed in Table 1. All the variables are seasonally adjusted, including calendar adjustments and outlier detection and correction. 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

[2] 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.

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.

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 since factor models is still a developing area. For instance, Boivin and Ng (2006), have found that selecting a smaller subset of the available large data sets, and using the factors summarizing 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, from those previously considered, 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.

The coincident indicator along with shaded areas that refer to the NBER recessionary periods are plotted in Figure 1. According to the findings of Stock and Watson (1991), 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.

Aruoba and Diebold (2010) use the extension proposed by Mariano and Murasawa (2003) to include indicators of mixing frequencies and indicators that may start at different periods and that may exhibit different publication lags. 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

[3] All the dynamic factor models use $p1= p2=p3=2$.

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. Although the aim of the paper is to examine the performance of the model in GDP forecasting, it is worth checking that the coincident indicator provided by the models exhibit similar accuracy to describe the US business cycle as the seminal Stock-Watson indicator. According to Figure 2, the Aruoba-Diebold and the Stock-Watson indicators exhibit high concordance.

The delay in the publication some of these five indicators makes it interesting to check if the forecasting performance of the economic activity can be improved upon in real time by including early available additional indicators. For this purpose, manufacturing new orders and some soft indicators such as consumer confident and PMI manufacturing were included in the model. In addition, due to their role in the recent downturn, houses started and SP500 were also analyzed. 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 stay around 75%.[4]

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 cycle dynamics in h periods. To select the number of leads, we compute the log likelihood associated with lead times that go from zero months to 24 months. Figure 1, shows that the maximum of the likelihood function is achieved when the term spread leads the common factor by six months. The estimated loading factor of the model that includes the term spread leading the factor by six months, which is displayed in the row labeled as M6 in Table 2, shows it is not statistically significant. We left the final decision about the use of the term spread in dynamic factor models to compute short-run forecasts of GDP to the section devoted to the real-time forecasting analysis.

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 cycles, let us assume that there is a regime switch in the index itself. For this purpose, we assume that the switching mechanism of the common factor at time t, x_t, is controlled by an unobservable state variable, s_t, that is allowed to follow a first-order Markov chain. Following Hamilton (1989), a simple switching model may be specified as:

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

where $\varepsilon_t \sim iidN(0,\sigma)$.[5] 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, χ_{t-1}, and of the business cycle states prior to t-1. Accordingly, the probabilities of staying in each state are

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

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 the related literature, expansions are more persistent than downturns (estimated p_{00} and p_{11} of about 0.98 and 0.92, respectively). These estimates are in line with the well-known fact that expansions are longer than contractions, on average. Finally, Figure 3 displays the estimated smoothed probabilities of recessions and 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.

3.3. Simulated real-time analysis

Testing predictive performance of forecasting models may be evaluated by means of several methods. First, by conducting *in-sample* estimates whereby one may check how well the time series path (common factor) tracks current-quarter GDP (recall section 3.2). However, very parsimonious models tend to explain the past of some variables much better than they do

[4] The loading factor of other indicators such as non manufacturing PMI, were not statistically significant.
[5] According to Camacho and Perez-Quiros, 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.

whenever they forecast such variables' future[6]. As a result, conducting *in-sample* evaluations would become inappropriate in order to fully validate the model.

To add some confidence on real forecasting evaluation of single-index dynamic factor models, we proceed to test the model's performance by forecasting unknown data. As proposed by Stark and Croushore (2002), the second (and optimal) methodology would be testing its performance using information available in every single forecast moment, what is called in *real-time.* However, historical time series - in *real-time*- are not usually available.

Consequently, some researchers undertake a third methodology: which is commonly known as *out-of-sample* forecasts. Such forecasts are conducted using database built upon those historical time series available at every moment (whenever the analysis is conducted), but erasing every single time the data released from them on. Although an appropriate database - to conduct such evaluation - become easy to build, Stark and Croushore (2002) show that the statistical power of *out-of-sample* evaluations is generally much higher than those obtained using databases in *real-time*. The reason behind has to do with updates. Broadly speaking, *out-of-sample* forecasts are conducted including updated (after every single forecast) time series. Nevertheless, *out-of-sample* databases usually do not take into account the fact that not all time series are available at forecasts moment due to typical delays which time series suffer.

As a result, one may easily infer that short-term forecasts for U.S. GDP face two major challenges:

- Data releases of GDP occur with a considerable delay: the advanced estimate of U.S. GDP is published several weeks after the end of the quarter. At the same time, there arrives a bulk of monthly data on real activity in the same quarter, which is published earlier. There are gains therefore in making use of this information when producing short-term forecasts for GDP.
- These monthly data are however themselves published with different delays. As summarized in Table 1, survey and financial data are available right at the end of the month, while industrial production data are published with a delay of 6 weeks.

Finally, a reasonable alternative to *out-of-sample* forecasts analysis is the use of *pseudo real-time* databases. The *pseudo real-time* forecast evaluation exercise takes full account of the timing of data releases. The term "*pseudo*" is used, because the data are downloaded on a certain day. Hence, subsequent revisions to the initial data releases are

[6] See Stark and Croushore (2002) for further details.

ignored. However, the *real-time* data availability patterns are fully replicated when producing the recursive forecasts. Such strategy is commonly used in previous related literature as in Giannone et al (2008) and Camacho and Doménech (2012), obtaining good results.

To be completed.

4. Conclusions

This paper proposes an extension of the Stock and Watson (1991) single-index dynamic factor model adding two refinements to the baseline method of monitoring developed by Auroba and Diebold (2010), and evaluates it for forecasting exercises of the US quarterly GDP growth. The model has the advantage of combining soft and leading indicators such as financial time series, with different frequencies and publication lags. Our model computes estimates of the unobserved common coincident component by using the Kalman filtering.

Our main results indicate three interesting features. First, we find that enlarging the baseline model does not lead to any distortion in computing the business cycle coincident indicator. However, soft indicators lead to substantial improvements in the ability of the model to capture the US business cycle dynamics. Second, we show that financial indicators are not useful for forecasting US output growth, in line with Wheelock and Wohar (2009), who find that the term spread to forecast output growth has diminished in recent years. Finally, following Camacho and Domenech (2012) we are still working to provide a simulated real-time exercise (pseudo real-time, out of sample) so that we may eventually validate our model and prove that the model is a very useful tool for the short-term forecast of the US economy. Conclusions section, therefore, remains to be completed.

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 $Y_t = \left(y_t^*, Z_{it}^*, Z_{ft}^*\right)'$. For simplicity 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

$$\begin{pmatrix} y_t^* \\ Z_{it}^* \\ Z_{ft}^* \end{pmatrix} = \begin{pmatrix} 0 & \frac{\beta_y}{3} & \frac{2\beta_y}{3} & \beta_y & \frac{2\beta_y}{3} & \frac{\beta_y}{3} & \frac{1}{3} & \frac{2}{3} & 1 & \frac{2}{3} & \frac{1}{3} & 0 & 0 \\ 0 & \beta_i & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ \beta_f & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x_{t+1} \\ x_t \\ \vdots \\ x_{t-4} \\ u_t^y \\ \vdots \\ u_{t-4}^y \\ u_t^i \\ u_t^f \end{pmatrix}. \tag{A1}$$

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

$$\begin{pmatrix} x_{t+1} \\ x_t \\ \vdots \\ x_{t-4} \\ u_t^y \\ \vdots \\ u_{t-4}^y \\ u_t^i \\ u_t^f \end{pmatrix} = \begin{pmatrix} \rho_1 & \cdots & 0 & 0 & 0 & \cdots & & & 0 \\ 1 & & & 0 & & \cdots & & & 0 \\ \vdots & \ddots & & \vdots & & \cdots & & & \vdots \\ 0 & \cdots & 1 & 0 & & \cdots & & & 0 \\ 0 & \cdots & & 0 & d_1^y & 0 & 0 & & 0 \\ \vdots & \cdots & & \cdots & \ddots & & & & \vdots \\ 0 & \cdots & & & & 1 & 0 & & 0 \\ 0 & \cdots & & & & 0 & 0 & d_1^i & 0 \\ 0 & \cdots & & & & 0 & 0 & 0 & d_1^f \end{pmatrix} \begin{pmatrix} x_t \\ x_{t-1} \\ \vdots \\ x_{t-5} \\ u_{t-1}^y \\ \vdots \\ u_{t-5}^y \\ u_{t-1}^i \\ u_{t-1}^f \end{pmatrix} + \begin{pmatrix} e_{t+1} \\ e_t \\ \vdots \\ e_{t-5} \\ \varepsilon_{t-1}^y \\ \vdots \\ \varepsilon_{t-5}^y \\ \varepsilon_t^i \\ \varepsilon_t^f \end{pmatrix}, \tag{A2}$$

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

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Table 1: Final variables included in the model

	Series	Sample	Source	Publication delay	Data transform.
1	Real GDP (GDP)	60.1-11.1	Bureau Economic Analysis		SA, QGR
2	Industrial production (IP)	60.01-11.05	Federal Reserve Bulletin		SA, MGR
3	Employment (Empl)	60.01-11.05	Bureau Labor Statistics		SA, MGR
4	Real Personal Income Less Transfer Payments (Inc)	60.01-11.05	Bureau Economic Analysis		SA, MGR
5	Retail Sales and Food Services (sales)	67.01-11.05	Census		SA, MGR
6	Manufactures New Orders (MNO)	92.03-11.05	Census		SA, MGR
7	Consumer Confidence (CC)	67.02-11.06	Conference Board		SA, L
8	Manufacturing PMI	60.01-11.06	Institute Supply Management		SA, L
9	Housing Starts (House)	60.01-11.05	Census		SA, MGR
10	SP500 Stock Price Index (SP500)	60.01-11.06	NYT		MGR
11	Slope Yield Curve 10Y-Fed (Slope)	62.01-11.06	Treasury and FRB		L

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

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	0.25 (0.01)	0.59 (0.03)	0.54 (0.03)	0.35 (0.04)	0.22 (0.02)	0.28 (0.03)	0.06 (0.02)	0.04 (0.02)	0.10 (0.02)	0.11 (0.03)	---	77.30%
M7	0.25 (0.01)	0.59 (0.03)	0.54 (0.03)	0.35 (0.04)	0.22 (0.02)	0.28 (0.03)	0.06 (0.02)	0.04 (0.02)	0.10 (0.02)	0.11 (0.04)	-0.01 (0.02)	77.36%

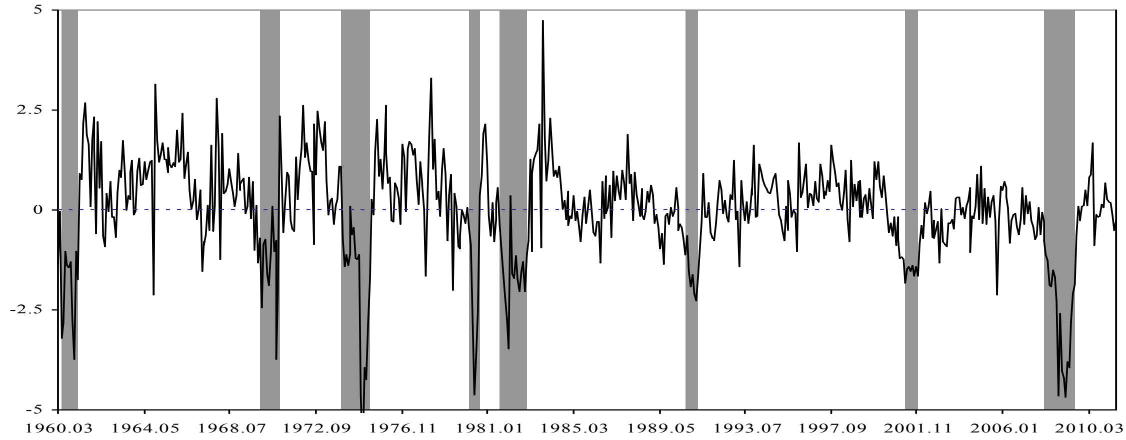
Notes. Factor loadings (*t*-ratios are in parentheses) measure the correlation between the common factor and each of the indicators appearing in columns. See Table 1 for a description of the indicators.

Table 3. Markov-switching estimates

c_0	c_1	σ^2	p_{00}	p_{11}
0.39 (0.04)	-1.94 (0.11)	0.89 (0.05)	0.98 (0.01)	0.92 (0.02)

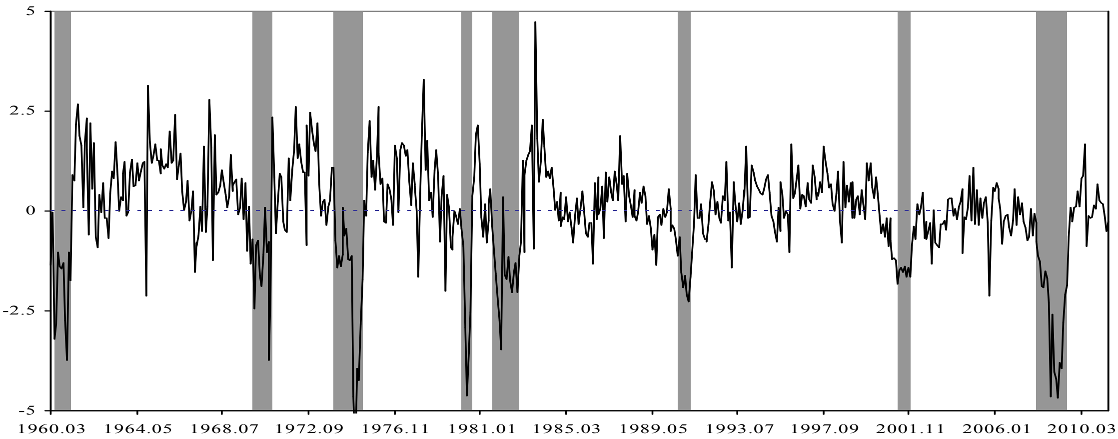
Notes. The estimated model is $x_t = c_{s_t} + \varepsilon_t$, where x_t is the common factor and $\varepsilon_t \sim iidN(0,\sigma)$, and $p(s_t = i/s_{t-1} = j) = p_{ij}$.

Figure 1. Common factor from Stock-Watson model



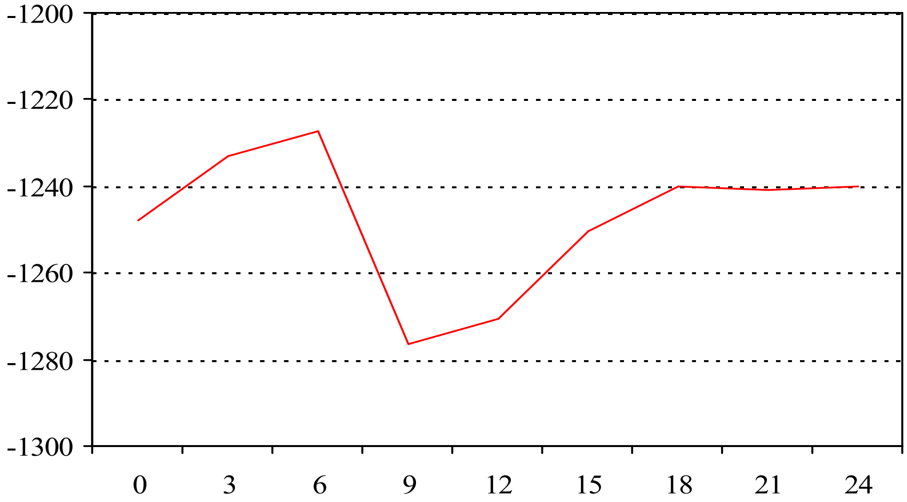
Notes: The factor model is estimated by using industrial production, employment, income and sales. Shaded areas correspond to recessions as documented by the NBER.

Figure 2. Common factor from Aruoba-Diebold model



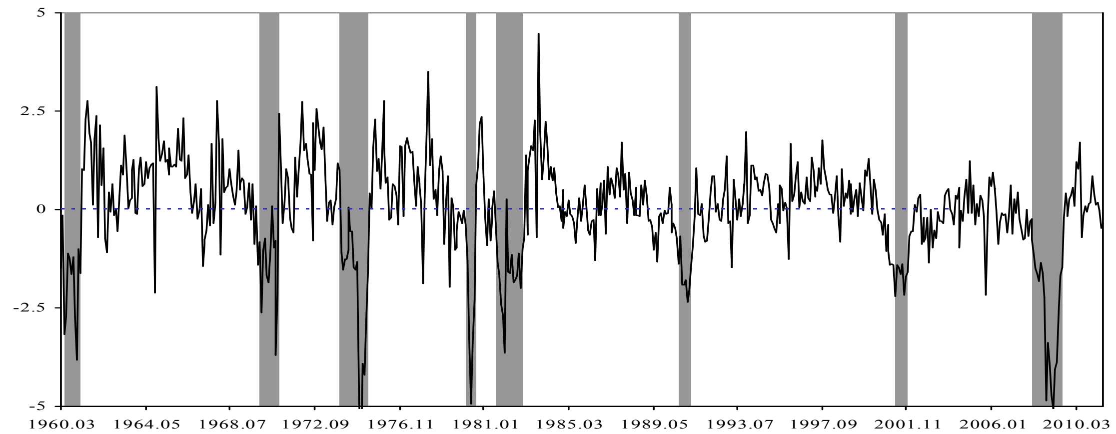
Notes: Apart from the indicators listed in Figure 1, the factor model is estimated by including real GDP. Shaded areas correspond to recessions as documented by the NBER.

Figure 3. Log likelihood and lead time of the term spread



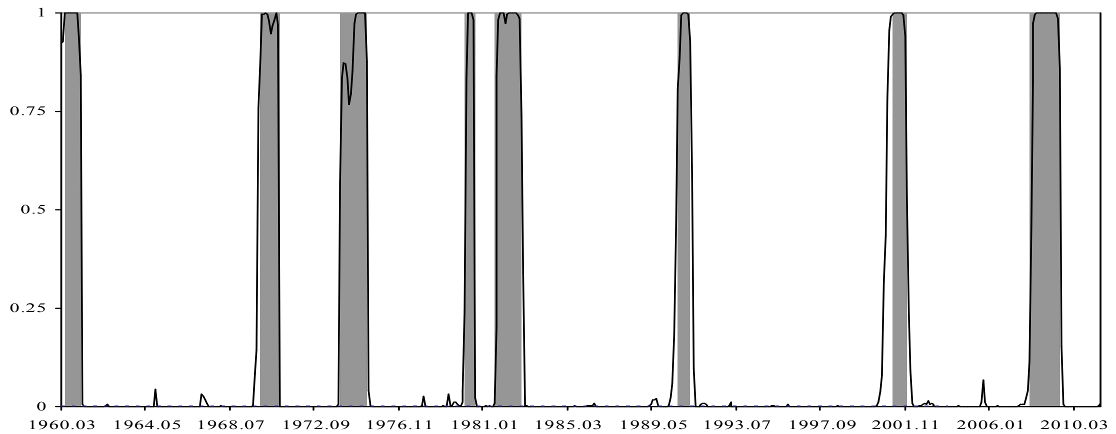
Notes. The term spread at time *t* has been related to the common factor at time *t*+*h*. In this figure, *h* appears in the horizontal axis and the log likelihoods reached by the dynamic factor model appear in the vertical axis.

Figure 4. Common factor from our model



Notes: Apart from the indicators listed in Figure 2, the factor model is estimated by including manufacturing new orders, consumer confident, manufacturing PMI, houses started, and SP500. Shaded areas correspond to recessions as documented by the NBER.

Figure 5. Filtered probabilities from common factor



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