Spanish diffusion indexes[1]

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Abstract

We use the Stock-Watson diffusion index methodology to summarize the information contained in a wide set of monthly series (published in the Statistical Bulletin of the Bank of Spain) by means of a reduced number of factors. We find that the first two factors may be used as indicators of the core inflation and the business cycle dynamics of the Spanish economy, respectively. In addition, we study the effects of incorporating large information sets for the analysis of monetary policy. Finally, we show that forecasting prices and output with our factors outperforms other standard alternative forecasting procedures.

Key words: Diffusion indexes, business cycle analysis, macroeconomic forecasting.

JEL codes: E31, E32, E37.

1 Introduction

At the end of 1998, the Governing Council of the European Central Bank (ECB) announced price stability over medium term as the primary policy target of the Eurosystem. The basis for this monetary policy strategy relies on two key elements, later known as the two pillars: the analysis of the evolution of M3 in parallel with a broadly-based assessment of the outlook for future price developments. This two-pillar strategy implies that, in conducting its monetary policy, the ECB should monitor a large number of variables including, *inter alia*, wages, exchange rates, real activity measures, fiscal policy indicators, prices and cost indexes, and business surveys.

Two empirical problems arise from the practical implementation of such a policy, however. On the one hand, due to recent advances in information technologies, data are becoming increasingly available with unprecedented complexity and degree of disaggregation. The premise that the ECB should be expected to base its evaluation of price evolution on the analysis of a broad array of time series in a timely manner with no lose of relevant information, is inevitably difficult to carry out. Fortunately, Forni *et al.* (2000), and Stock and Watson (2002) have shown that the information contained in large data sets can be properly summarized using dynamic factor models, where a small number of unobserved common factors may capture the comovements across the series. In addition, these authors have successfully employed the factors to forecast macroeconomic time series with particular success in forecasting inflation. On the other hand, the ECB policy focuses on the evolution of the Euro-area aggregates as a whole, rather than on the dynamics of macroeconomic variables of single member countries. However, forecasting Euro-area aggregates is largely new territory and it must be decided whether to construct direct forecasts from the aggregate Euro-area variables or to pool country-specific forecasts from national databases. In this respect, Marcellino *et al.* (2002) conclude that there are significative gains from forecasting at the country level and to aggregate afterwards to the area-wide level, relative to forecasting directly with the Euro-area aggregates.

Within this context, the Bank of Spain has recently provided electronic access to all the historical time series relating to all the tables included in the Statistical Bulletin (*Boletín Estadístico*) in a readable file. In this paper, we use this collection of series, that constitutes one of the most exhaustive descriptions of the Spanish economy, to address the following questions. Firstly, from this wide range of economic variables, we extract a collection of common factors using the diffusion index model advocated by Stock and Watson (2002). Secondly, we develop a systematic evaluation of these factors in terms of their usefulness as indicators of the Spanish economy. We find that the first factor is highly correlated with nominal series (prices, wages, interest and exchange rates), and that the second factor is highly correlated with real series (output, capacity utilization, unemployment). This leads us to label these factors as the nominal factor and the real factor, respectively. In addition, we explore the comovements of these factors with several nominal and real macroeconomic Spanish series. Interestingly, we conclude that our nominal and real factors may be interpreted as Spanish indexes of the trend inflation and of the real economic activity respectively. Furthermore, we compare the dynamics of our factors with other Euro-area indicators to check for similarities and differences between their inflation and business cycle patterns. Third, we find that the inclusion of these factors into the estimation of a forward-looking Taylor rule, which approximates the fact that monetary policy is made in a data-rich environment, is used to characterize the monetary policy in Spain. Fourth, we assess to what extent the empirical factors may be used to forecast Spanish prices and output. We develop this analysis by computing the reduction in the mean square forecast errors with respect to other baseline forecasts, AR and VAR models, in a simulated out-of-sample exercise. In addition, we compute several tests described in Diebold and Mariano (1995) to compare the accuracy of these alternative forecasting procedures. On the one hand, we detect that the inflation forecasts implied by our factors significantly improve upon the benchmark forecasts. On the other hand, even though we find that the factors produce lower forecast errors to predict output growth, the improvements become statistically significant only for forecasting horizons longer than six months.

We organize the paper as follows. In Section 2, we summarize the main features of the dynamic factor model. In Section 3, we develop a preliminary analysis of the Bank of Spain data set. In Section 4, we describe the main characteristics of our empirical factors, analyze their ability as nominal and real Spanish indicators, study their uselfulness to the analysis of monetary policy, and check their inflation and output growth forecasting accuracy. In the last Section, we conclude and propose some lines for further research.

2 The diffusion indexes model

A natural approach to handle large data sets is the factor model of Sargent and Sims (1977), Geweke (1977), and Geweke and Singleton (1981). In this dimension-reduction technique it is assumed that a set of N variables x_t, observed for $t = 1, ..., T$, may be represented as the sum of two mutually orthogonal unobservable components: the common r-dimensional component f_t and the idiosincratic N-dimensional component e_t:

$$x_t = \Lambda f_t + e_t, \tag{1}$$

where Λ is the $(N \times r)$ factor loading matrix relating the common factors to the observed series. This representation has the advantage that the factors can be estimated using the standard method of principal components, and nests models where x_t depends on lagged factors. Thus, being X and F the $(T \times N)$ and $(T \times r)$ standard stacked forms of x_t and f_t, the estimated factors are $\widehat{F} = X\widehat{\Lambda}/N$, where $\widehat{\Lambda}$ is equal to $N^{1/2}$ times the eigenvectors of $X'X$ corresponding to its r largest eigenvalues.

Recently, Forni *et al.* (2000), and Stock and Watson (2002) have provided theoretical, computational and empirical contributions leading to reconsider the macroeconomic application of this method. Firstly, from a theoretical point of view, these authors have adapted the factor model to the analysis of large cross section and allow the idiosincratic component to exhibit both temporal and limited cross sectional dependence. In particular, Stock and Watson (2002) have shown that the space spanned by the factors may be estimated consistently by principal components, and that the forecasts generated by these factors are first order asymptotically efficient. Two key conditions for the latter result to hold is that the number of factors included in the estimated model has to be either equal to or larger than the number of non-redundant common factors r, and that the cross section dimension must be much greater than the time dimension; that is $N >> T$.[1]

Secondly, Stock and Watson (2002) have made an important computational contribution by extending the factor model to deal with the problem of missing data.[2] In practice, their EM algorithm can be summarized as follows. First, they propose to get an initial estimate of the factors and loadings from the balanced panel (time series with no missing data). Second, these factors are used to provide an estimate of missing observations using (1). Third, new factors are obtained from the entire data

[1] As pointed out in the empirical application, we follow Stock and Watson (2002) to choose the underlying number of factors according to their forecasting performance.

[2] This problem specially affects the series considered in our Spanish data set: of our 1133 monthly series, 626 start too late or end too soon, and 312 present significant outliers that are treated as missing.

set with missing values replaced by their estimates. The process is then iterated until the estimates do not change substantially.

Thirdly, the dynamic factor model has been succesfully applied to forecasting macroeconomic series in the US (Stock and Watson, 1999, 2002), Canada (Gosselin and Tnacz, 2001), the Euro-area (Marcellino et al., 2002, and Angelini et al., 2001b), and the UK (Artis et al., 2001) economies. As a natural extension of the forecasting literature, Bernanke and Boivin (2000) have explored the benefits of using diffusion indexes in Taylor rule estimations providing an evaluation of the importance of the factors for a better understanding of monetary policy. Finally, the factor model framework has also been used in developing Euro-area indicators as in Forni *et al.* (2000, 2001), and Cristadoro *et al.* (2001).

3 Preliminary analysis of the data

The data used in this study are taken from the electronic version of the Statistical Bulletin issued by the Bank of Spain. This readable file contains more than 9000 time series of output, demand, employment, wages, prices, financial markets, financial accounts, interest rates, institutional groupings, and several international statistics. These series show a high degree of heterogeneity with regard to their frequency (364 are annual, 5 semi-annual, 3868 quarterly and 5202 monthly) and availability (some series start in the 40s and others in the 90s).

Prior to the application of the diffusion index model, it is essential to select both the periodicity and the effective sample period. We use monthly series since they allow for more frequent and updating reports and start the analysis in 1975.01 for two reasons: first, because that date allows to balance the trade-off between the benefit of working with sufficiently long time series for estimation and forecasting and the requirement of replacing missing starting observations. Second, because neither the indicators used to be compared with the extracted factors nor the series of production to be forecasted are available prior to that date. Thus, we consider a final data set including 1133 monthly series (509 balanced) spanning the period from 1975.01 to 2001.04.[3]

The Spanish monthly series show a pronounced seasonal component compared to other countries' monthly series. In line with Kaiser and Maravall (1999), we deal with seasonal patterns by using trend-cycle instead of seasonally adjusted transformations because the latter contain a highly erratic component which seriously disturbs their interpretation and makes them difficult to monitor. To illustrate this particular behavior, Figure 1 displays the evolution of the Spanish and US Industrial Production (IP) indexes, together with their seasonally adjusted and trend-cycle components. Chart 1 shows that the original Spanish series exhibits more dramatic seasonal slowdowns than the smoother US series. Chart 2 points out that the seasonally adjusted series is still very noisy for the Spanish economy. Chart 3 reveals that the trend-cycle component cleans the noise of the Spanish IP while the US

[3]We exclude from the analysis those series either starting after 1985.01 or having more than two-thirds of missing observations.

series remains almost unaltered.[4]

Finally, according to the method proposed by Stock and Watson (2002), we process the series as follows. First, we take into account possible heteroskedasticity by taking logarithms of nonnegative series that were not in rates or in percentage units. Second, we transform the series to account for stochastic trends by differencing the series if necessary. Third, we screen for significative outliers by considering as missing any observation exceeding six times the interquantile range from the median of the series. Fourth, we standardize all series to have zero mean and unit variance.[5]

4 Empirical results

4.1 Empirical factors

The EM algorithm iteratively estimates missing observations using the factors of the balanced panel as the starting point. This procedure involves the risk of substantial deterioration of the final factors obtained from the entire dataset. As documented in Angelini et al. (2001a, 2001b), the deterioration increases when the number of factors in each EM iteration is large. As they suggest, we fulfill missing observations using four factors. We show in Figure 2 that our final factors incorporate the main dynamic features of the balanced panel factors. Accordingly, the rest of the paper

[4] Seasonal transformations were computed with the TRAMO-SEATS program.

[5] Our final data set, including a code showing the transformation of each series, is described in the Appendix.

focuses on these final estimated factors.

An interesting feature of the factors is to analyze to what extent the factors are able to capture the variablility of the original series. In our study, we obtain that the first four (two) factors account for almost fifty (thirty) per cent of the variance of the data, and that the marginal contribution of each additional factor declines dramatically.

The final question addressed in this section is that of the correspondence of the estimated factors with the original series. Figure 3 plots the correlation between each of the individual series of the entire panel (grouped in chapters as in the Statistical Bulletin) and the first four factors. This points out the high correlation of the first factor with Spanish and foreign prices (chapters 25, 26, and 17), of the second factor with output, demand, unemployment, external trade, interest rates, and foreign output (chapters 23, 24, 17, 18, and 26), of the third factor with exchange rates and unit value indexes (chapters 19 and 17), and of the fourth factor with housing and wages (chapters 23 and 24), although correlations with the last two factors are weaker.

4.2 The first factor as a nominal indicator

Given the high correlation between the first factor and the series of prices, it is worth to consider the potential usefulness of this factor as a nominal indicator of the Spanish economy. In this respect, Figure 4 plots our first factor together with several macroeconomic time series of prices, and other Spanish and Euro-area nominal indexes. Chart 1 and 2 show the close relationship between our factor and two measures of price inflation: the rate of growth of Consumer Price Index (CPI) and Industrial Prices Index (*Indice de Precios Industriales*, IPRI). In addition, these charts point out that the volatility of our first factor is lower than the volatility of the price series, suggesting that our factor may be interpreted as a measure of the Spanish core or trend inflation. Chart 3 and 4 plot our factor along with other standard Spanish price indexes: the growth rate of the GDP deflator (GDPD) and the Harmonized Consumer Price Indexes (HCPI) respectively. Note that, even though our factor does not entail any backward time phase shift (as the HCPI does), it does present the desirable smoothness properties of any core inflation indicator. Chart 5 reveals the similarities between the evolution of our factor and the evolution of the growth rate of the Euro-area Harmonized Consumer Price Index (Euro-HCPI), that is the target series in the conduct of the ECB monetary policy. These simmilarities point out the nominal convergence of Spain with the Euro-area economy. Finally, Chart 6 plots this nominal factor along with the nominal factor obtained by Angelini et al. (2001b) using the dynamic factor method for the Euro-area economy. These series exhibit a similar pattern, although our indicator shows a lower volatility.

4.3 The second factor as a real indicator

Early detection of business cycle turning points has always been a major concern for consumers, policy makers, businessmen and investors, since the sequence of states determines their economic decisions to be optimal. This motivates many empirical researchers to look for indicators of the overall economic activity that help to identify emerging stages of the current business cycle. We investigate in this section the ability of our second factor as a new index for the Spanish business cycle.

To be more confident that our real factor is an economic activity indicator, we examine in Figure 5 the dynamic evolution of this factor and several real activity variables, other Spanish indexes, and Euro-area economic indicators. The first two charts of this figure reveal the high correspondence between the factor and two major real economy series: GDP growth rate (Chart 1) and minus unemployment growth rate (Chart 2). In addition, Chart 3 and Chart 4 plot the factor together with two Spanish business cycle indicators: the Synthetic Activity Indicator (*Indicador Sintético de Actividad*, SAI) elaborated by the Ministry of Economy (*Ministerio de Economía*), and the coincident indicator issued by the Spanish National Statistical Institute (*Instituto Nacional de Estadística,* INE). In both cases, these series exhibit striking similarities in their cyclical patterns. Finally, to compare national and Euro-area business cycles dynamics, we represent our national factor along with the EuroCOIN, the monthly indicator of the Euro-area business cycle published by the CEPR (Chart 5), and with the real European factor obtained by Angelini et al. (2001b) using a dynamic factor model approach. These charts show that, even though the Spanish economy has tended to move through largely synchronized business cycles, some noticeable differences appear.[6] This support the view that, while there are Euro-area fluctuations common to their members, country-specific business cycles movements still remain.

We now explore the patterns of comovement between our factor and the economic activity series depicted in Figure 5. In this respect, Figure 6 computes the cross correlations of each of these series at time t, with our real factor at $t+k$, with k taken values from -4 to 4 for quarterly series and from -12 to 12 for monthly series. We find that our real factor is highly correlated with all of these series confirming their high degree of business cycle conformability. In addition, we find that the Spanish factor appears to lead the euro indicators, which agrees with the results of Artis et al. (1997) who find that Spanish business cycles are more contemporaneously correlated with US cycles than with European cycles, which typically lag the US turning points.

We turn next to examine whether our factor leads similar business cycle characteristics than those implied by other Spanish and European indicators. In particular, we analyze the presence of two business cycles characteristics: steepness and deepness. The former is characterized by gradual upward slopes during expansions and steep downward slopes during recessions. The latter is characterized by relatively

[6] One of these differences is the negative average growth of the Euro-area indicators in 1998 versus the positive average growth of the Spanish indicators in this year.

deep troughs and low peaks. Sichel (1993) argued that stationary time series exhibiting steepness (deepness) should present negative skewness in levels (first differences). This leads the author to propose the following simple test to detect the presence of these asymmetries. First, construct a variable whose t-th observation is

$$o_t = (c_t - \overline{c})^3 / \sigma(c)^3, \tag{2}$$

where c_t is the level (first differences) of the stationary series to test for steepness (deepness), $\overline{c}$ is its sample mean, and $\sigma(c)$ is its sample standard deviation. Second, regress this variable on a constant and compute its Newey-West standard error. Finally, the estimate of the constant divided by this standard error is asymptotically normal. Table 1 reveals that, as evidenced by the high p-values, our factor fails to detect evidence of business cycles asymmetries at any reasonable critical level. This finding holds using other economic indicators referred to Spain (SAI and INE indicators) and the Euro-area (the EuroCOIN and the indicator of Angelini et al., 2001b).

Finally, it is standard to look for an appropriate filter to convert the information contained in economic indicators into more intuitive series of recessions probabilities (for an extensive overview, see Camacho and Perez-Quiros, 2002). As shown in Figure 2, our factor exhibits a negative trend during the late 70's and early 80's, the late 80's and early 90's, the middle 90's, and the late 90's, and a positive trend elsewhere. Note that this dynamics highly corresponds with the timing of the (broadly accepted) Spanish business cycle phases. According to this particular behavior, we fit the following two-state Markov-switching model for the real activity factor:

$$\widehat{f_t} = \widehat{c}_{s_t} + \underset{(0.06)}{1.61} f_{t-1} - \underset{(0.10)}{1.09} f_{t-2} + \underset{(0.12)}{0.49} f_{t-3} - \underset{(0.12)}{0.07} f_{t-4} - \underset{(0.10)}{0.14} f_{t-5} + \underset{(0.05)}{0.17} f_{t-6}, \quad (3)$$

where the estimates of the switching intercept are $\widehat{c}_1 = \underset{(0.02)}{0.07}$ and $\widehat{c}_2 = \underset{(0.02)}{-0.04}$, the estimate of the variance is $\widehat{\sigma}^2 = \underset{(0.001)}{0.017}$, and the estimates of the transition probabilities governing the Markov process are $\widehat{p} = \underset{(0.03)}{0.94}$ and $\widehat{q} = \underset{(0.02)}{0.97}$, with standard errors in parentheses.[7] We find that the estimate of the intercept is positive within the first state and negative within the second state. This confirms the asymmetric behavior of the factor and suggests that states 1 and 2 may be interpreted as expansions and recessions respectively. To show this point, Figure 7 (Chart 1) displays the high correlation between negative values of the weighted average estimated intercept (weights are the smoothed probabilities) and the recessionary periods obtained in an independent work by Bengoechea (2000).[8] In addition, Figure 7 (Chart 2) plots the smoothed probabilities of being in recessions together with Bengoechea's recessionary periods. It is worth mentioning that, even though our approaches are completely independent, there are strong similarities between the two business-cycle dating. Artis *et al.* (1999) lead to similar Spanish recessionary periods applying the Markov-switching approach to the series of industrial production. Note that we find that the smoothed probability of recession increases dramatically since early 2000 which coincides with the peak fixed by the OECD at 2000.02 for the Spanish

[7] The lag length have been chosen according to the BIC information criterium.

[8] This author uses the NBER methodology to date the Spanish business cycle turning points during the period 1970-1999. Shaded areas correspond to her recessionary periods.

economy. Finally, an interesting application of the Markov framework is that the expected number of months that a recession prevails may be computed from the model estimates. Conditional on being in state 2, the expected duration of a typical Spanish recession is $(1-q)^{-1}$ or 33 months, similar to the 28 months estimated by Artis *et al.* (1999).

4.4 Monetary policy and factor models

Even though the increasing availability of economic time series, the majority of empirical monetary policy studies employ structural VAR models (SVAR) and Taylor rules reaction functions. However, these models implicitly assume that monetary authorities only exploit the limited amount of information contained in a reduced number of variables. As noted by Bernanke and Boivin (2001), the divergence between the central bank practice and academic research could lead to less accurate econometric evaluation of central bank policies.

Compared to the limited information context usually employed in this literature, we examine to what extent incorporating the information of large data sets may lead to contradictory results about the instrumentation of the Spanish monetary policy during the period $1984.01-1998.05$. Specifically, we compare the estimates of a forward-looking taylor rule where factors are not included among the monetary policy instruments with those estimates obtained in an alternative scenario where factors are used as instruments. Following López (2002), we consider the following

Bank of Spain reaction function:

$$i_t = \rho i_{t-1} + (1-\rho)[\alpha_1 D_{84-92} + \alpha_2 D_{93-98} + \beta(E_t \pi_{t+12} - \pi^*_{t+12}) + \gamma(y_t - y^*_t)] + \varepsilon_t, \tag{4}$$

where i_t is the three-month interbank market rate, D_{84-92} (D_{93-98}) is a dummy variable that takes value one in $1984.01 - 1992.12$ ($1993.01 - 1998.05$) and zero elsewhere, π is the inflation rate, π^* is the inflation target measured by the official inflation rate in the budget laws up to 1995 and the target inflation rate of the Bank of Spain since 1996, and $(y - y^*)$ is the output gap measured by the deviations of the (log of) Industrial Production Index from its trend computed using the Hodrick-Prescott filter.[9] The lagged dependent variable i_{t-1}, is included to capture the central bank interest-rate smoothing behavior.[10]

Equation (4) is estimated by GMM using two different sets of instruments. First, we include six lags of the Spanish and German interest rate along with twelve lags of the inflation rate and the output gap series. Second, we add to the prior list six lags of our nominal and real factors. Estimation results are shown in the first two rows of Table 2. When we do not include the factors within the set of instruments (first row), the parameter estimates show that the interest rate responds less than proportionally to deviations of inflation from its target ($\widehat{\beta} = 0.69$). This seems to indicate that the Bank of Spain has followed an accommodative monetary policy during the sample period. However, when we add our factors to the instruments list

[9] We consider the standard smoothing parameter of 14400, corresponding to monthly series.

[10] See Lowe and Ellis (1997) for details about the motivation of the interest rate smoothing.

(second row), the interest rate response to the inflation gap is significantly greater than one ($\widehat{\beta} = 2.18$). In this case, monetary policy seems to be agressive rather than accomodative.[11] In this respect, López (2002) leads to a similar result: under the perfect information assumption (third row of Table 2) he finds that the Bank of Spain follows an accomodative monetary policy ($\widehat{\beta} = 0.87$). However, when he includes the information available in real time, he concludes that the central bank conducts an aggresive policy ($\widehat{\beta} = 2.84$). This agrees with our previous finding: the estimation of Taylor rules in a limited information context may lead to misleading conclusions about the instrumentation of the monetary policy. Using the information included in real-time and large data sets may approximate the "data-rich environment" on which central bankers are expected to base their policy decisions. According to our empirical results, this information plays an important role in evaluating how central bankers have conducted their monetary policy.

4.5 Forecasting

In this section, we investigate the accuracy of our empirical factors to forecast two key macroeconomic variables: prices and output. For this attempt, we propose the

[11] In addition, if we do not consider the empirical factors, the output gap estimated coefficient is 0.31 and non-significant. However, if we include the factors in the set of instruments, the estimate is 1.43 and highly significant, so we conclude that the Bank of Spain was concern about the cyclical position of the economy.

following multi-step ahead forecasting procedure

$$y_{t+h}^h = \alpha_0 + \alpha_1 t + \sum_{j=0}^{m} \beta_j' \widehat{f}_{t-j} + \sum_{j=0}^{v} \gamma_j z_{t-j} + \varepsilon_{t+h}^h. \tag{5}$$

In this equation, y_{t+h}^h is the h-step ahead covariance stationary transformation of the original series y_t, so if this series is I(1), then $y_{t+h}^h = (\frac{12}{h}) \ln(y_{t+h}/y_t)$. Expression z_{t-j} is the j-lagged covariance stationary transformation of y_t, where $z_t = 12 \ln(y_t/y_{t-1})$ in the case of I(1) series. These lagged values are considered in parallel with standard autoregressive processes. Estimated factors and their lagged values are collected in the $(r \times 1)$ vectors $\widehat{f}_{t-j}$, with $j = 0, 1, ..., m$. Including the estimated factors allows us to analyze their additional predictive power. In addition, following the systematic approach to nonstationary series described in Dolado et al. (1990), we have detected that both the inflation rate and our nominal factor are covariance stationary around a small but statistically significant trend. Thus, according to Stock and Watson (1989), we have explicitly included a deterministic trend in the original forecasting specification since this increases its marginal predictive power. The term ε_{t+h}^h is a homoskedastic martingale difference sequence with respect to the set of information at time t. Finally, in line with previous studies in forecasting with empirical factors, our model is allowed to choose values of r lying between 1 and 4, and values of m and v lying between 1 and 6 based upon the BIC selection criterium.[12]

[12] Note that, with respect to the usual "one-step ahead projection", this "h-step ahead projection" approach eliminates the need for estimating additional equations for simultaneously forecasting $\widehat{f}$ and z.

Table 3 examines the gains of forecasting (3, 6, and 12 months ahead) with the estimated factors instead of forecasting with simpler small-scale models in a simulated out-of-sample exercise over the period $1997.01 - 2001.04$.[13] That is, in each out-of-sample forecast outliers are detected, missing observations are treated, factors are reestimated, and m and v in the forecasting equation are selected by BIC. On the one hand, among these small-scale models we include AR models, that are obtained by imposing $m = 0$ in the forecasting equation, and VAR models (the natural stacked generalization of the AR model) for the first differences of output and prices.[14] On the other hand, we show the Mean Square Errors (MSE) of any candidate forecasting model relative to the MSE of the AR forecasts. To be more confident about the relative gains of forecasting with the empirical factors, we compute several predictive accuracy tests. In particular, we consider two tests of the null of no difference in the forecast accuracy of two competing forecasting models: the Diebold and Mariano (1995) asymptotic test (DM henceforth) and the Morgan-Granger-Newbold small-sample test (MGN henceforth). In addition, we compute the exact finite-sample Wilconson's Signed-Rank test (WSR henceforth).[15]

With respect to the predictive performance on prices, Table 3 reveals several interesting results. First, the MSE of the VAR forecasts are either greater than (3

[13]The term *simulated* indicates that the series used in these operations are obtained at the end of the sample. This omits previsions and changes in the series occurring in true real-time.

[14]Both Engle-Granger and Stock-Watson common trends tests fail to detect cointegration between these variables. These results are omitted but available from the authors upon request.

[15]These three tests are extensively discussed in Diebold and Mariano (1995).

months ahead) or almost equal to (6 and 12 months) the AR forecast errors. Second, using the estimated factors to forecasting prices reduces the MSE with respect to the simpler AR predictions. Third, the relative gains of forecasting with factors become considerable when these forecasts are made with factors obtained from the total panel. That is, using the EM algorithm to complete unbalanced panels leads to more accurate forecasts. Fourth, these gains increase with the forecasting horizon, leading to MSEs that are one-third less than those of the AR model. Finally, the three tests proposed to compare the predictive accuracy show that the forecasting improvements of the DI model are statistically significant.

With respect to the predictive performance on output, the results are more ambiguous. As in the case of prices, forecasting with the factors reduces notably the MSE. This is specially important for forecasting horizons of more than 6 months with MSE reductions of up to the one-half. Using the asymptotic DM test these gains are only weakly significant at forecasting 12 months ahead (p-value of 0.07). However, both MGN and WSR tests, with p-values less than or equal to 0.05 for 6 and 12 forecasting horizons, reveal stronger evidence in favor of the statistical improvements of forecasting output using the estimated factors.

5 Conclusion

The ECB faces two empirical problems in the assessment of price stability: how to combine the increasing amount of available information and how to forecast Euro-area inflation. The former may be overcomed by using the diffusion index model advocated by Stock and Watson (2002). The latter has been analyzed by Marcellino *et al.* (2002). They recommend that each country member may construct national price forecasts to be aggregated to the Euro-area.

We contribute to this empirical literature by analyzing the ability of the diffusion index model to synthesize the information contained in the monthly series of the Bank of Spain's Statistical Bulletin in a reduced number of factors to be used in forecasting Spanish prices and output. We detect that the first two factors are highly correlated with nominal and real variables respectively. We further compare the evolution of these factors with several Spanish and Euro-area indicators and we conclude that our factors may be used as nominal and real activity indicators. We examine the consequences of including this "data-rich environment" into the analysis of the Spanish monetary policy during the period 1984.01−1998.05. Finally, we show that our estimated factors are useful for out-of-sample (period 1997.01 − 2001.04) forecasting Spanish inflation rate and output growth.

We consider that our results seem to be promising enough to warrant further research. Specifically, we are interested in investigating the application of diffusion index models to extract regional factors from series of each of the 17 Spanish Autonomous Regions. This research may be useful to check the relevance of region-specific versus area-wide information for macroeconomic forecasting as in Marcellino et. al (2002).

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Table 1. Business cycle asymmetries

Indicator	Null Hypothesis	Statistic	p-value
Real factor	No deepness	-0.0390	0.4555
	No steepness	-0.3103	0.2475
SAI	No deepness	-0.2909	0.2724
	No steepness	0.2556	0.1868
INE	No deepness	0.1015	0.4101
	No steepness	0.3395	0.2610
EuroCOIN	No deepness	-0.5299	0.2050
	No steepness	-0.3580	0.2148
AHM	No deepness	0.0030	0.4981
	No steepness	-0.0841	0.4269

Note: These tests, described in Sichel (1993), are based on the premise that stationary time series exhibiting steepness (deepness) should present negative skewness in levels (first differences). They are applied to the following series: our real factor, the Spanish Synthetic Activity Indicator (*Indicador Sintético de Actividad*, SAI), the coincident indicator issued by the Spanish National Statistical Institute (*Instituto Nacional de Estadística,* INE), the EuroCOIN, the monthly indicator of the Euro-area business cycle published by CEPR, and the real European factor obtained by Angelini, Henry and Mestre (2001b, AHM) using a dynamic factor model approach.

Table 2. Monetary policy analysis

	ρ	β	γ	J-test (p-value)
Perfect information	0.96 (0.01)	0.69 (0.63)	0.31 (0.30)	0.99
Perfect information with estimated factors	0.97 (0.01)	2.18 (0.63)	1.43 (0.46)	0.99
Perfect information (López, 2002)	0.93 (0.01)	0.87 (0.29)	0.03 (0.08)	0.98
Real time information (López, 2002)	0.95 (0.01)	2.84 (0.56)	0.50 (0.02)	0.99

Note: Following López (2002) this Table presents the estimates of the Bank of Spain reaction function

$$i_t = \rho i_{t-1} + (1-\rho)[\alpha_1 D_{84-92} + \alpha_2 D_{93-98} + \beta(E_t \pi_{t+12} - \pi^*_{t+12}) + \gamma(y_t - y^*_t)] + \varepsilon_t,$$

The estimation method is GMM and the sample period 1984.01 − 1998.05. The instruments used to obtain the estimates shown in the first row are six lags of the Spanish and German rate and twelve lags of the inflation rate and the output gap series. To obtain the estimates shown in the second row, we additionally consider six lags of the nominal and real factors as intruments. Third and fourth rows show the estimates obtained by López (2002) using perfect information and real time information respectively. Robust standard errors are shown in parenthesis below the coefficients estimates.

TABLE 3. Out-of-sample predictive performance

Forecast horizon		3			6			12		
Model		DI-b	DI-t	VAR	DI-b	DI-t	VAR	DI-b	DI-t	VAR
prices	RMSE	0.8678	0.6586	1.6660	1.1342	0.4092	0.9417	0.7965	0.3330	0.9601
	DM	0.3149	0.0115	0.0001	0.6504	0.0001	0.4687	0.6434	0.0001	0.0028
	MGN	0.1872	0.0000	0.0001	0.5829	0.0000	0.4692	0.3119	0.0000	0.2257
	WSR	0.0000	0.0000	0.8213	0.0005	0.0000	0.0005	0.0061	0.0000	0.0000
output	RMSE	0.7334	0.7429	1.0039	0.6934	0.6255	0.9806	0.5469	0.5787	1.014
	DM	0.3539	0.2927	0.9057	0.2840	0.1654	0.4519	0.0862	0.0686	0.3214
	MGN	0.0411	0.0228	0.9469	0.0328	0.0031	0.7287	0.0013	0.0020	0.3044
	WSR	0.1713	0.1713	0.0130	0.0519	0.0519	0.0969	0.0005	0.0001	0.3549

Note: Entries in rows one and five are the ratio of the Mean Square Error (MSE) of each candidate forecasting model over the MSE of the univariate autoregressive model. Other entries show the p-values of Diebold-Mariano (DM) test, Morgan-Granger-Newbold (MGN) test, and Wilconson's Signed-Rank (WSR) test, computed for each of these competing models. DI refers to the diffusion index model from the balanced panel (DI-b) and the total panel (DI-t). The balanced panel uses 197 monthly series with no missing observations whereas the total panel uses 1133 monthly series. VAR refers to vector autoregressive models including output and prices. "Out-of-sample" refers to the period 1997.01 – 2001.04.

Figure 1. Industrial production index: USA vs. Spain

Chart 1. Non seasonal adjusted

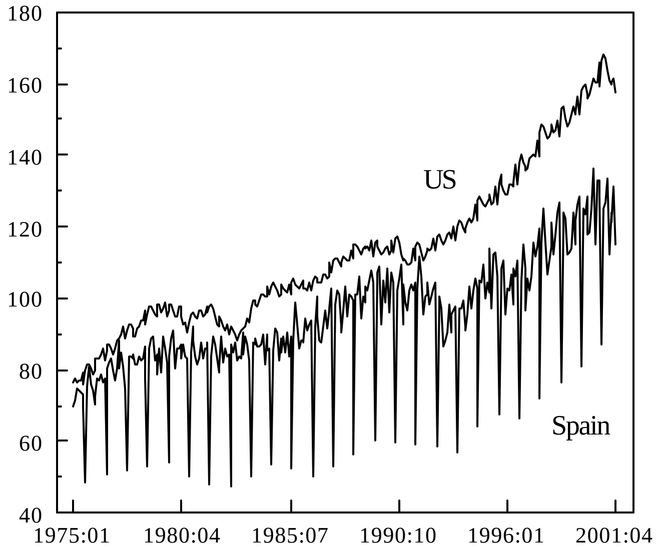


Chart 2. Seasonal adjusted

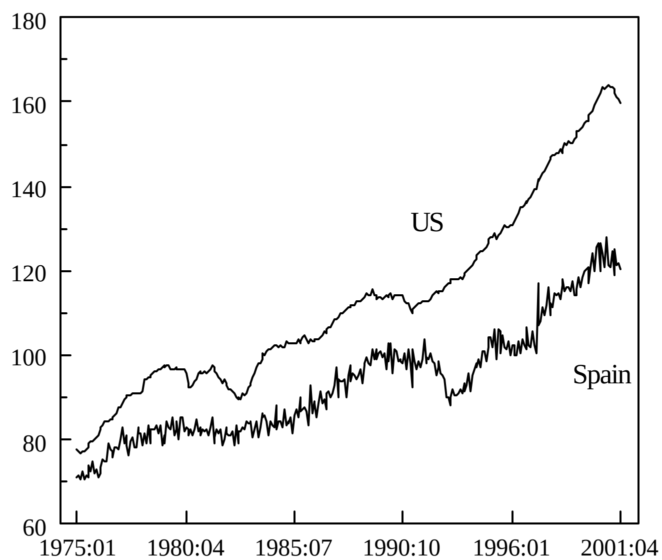
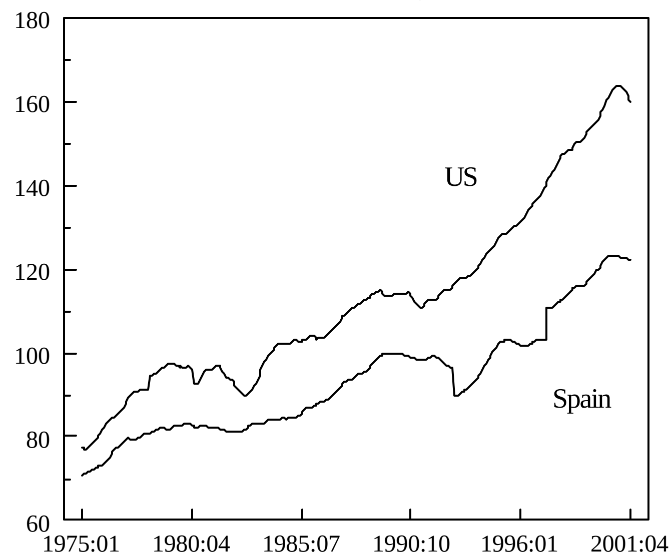


Chart 3. Trend-cycle.



Note. Figure 1 displays the Spanish and US Industrial Production index (IP) monthly series from 1975:03 to 2001:04. Chart 1, Chart 2 and Chart 3 refer to the original, seasonally adjusted, and trend-cycle series respectively. These transformations have been made using the TRAMO-SEAT program.

Figure 2. EM algorithm effects

Chart 1. First factor from balanced and final panels

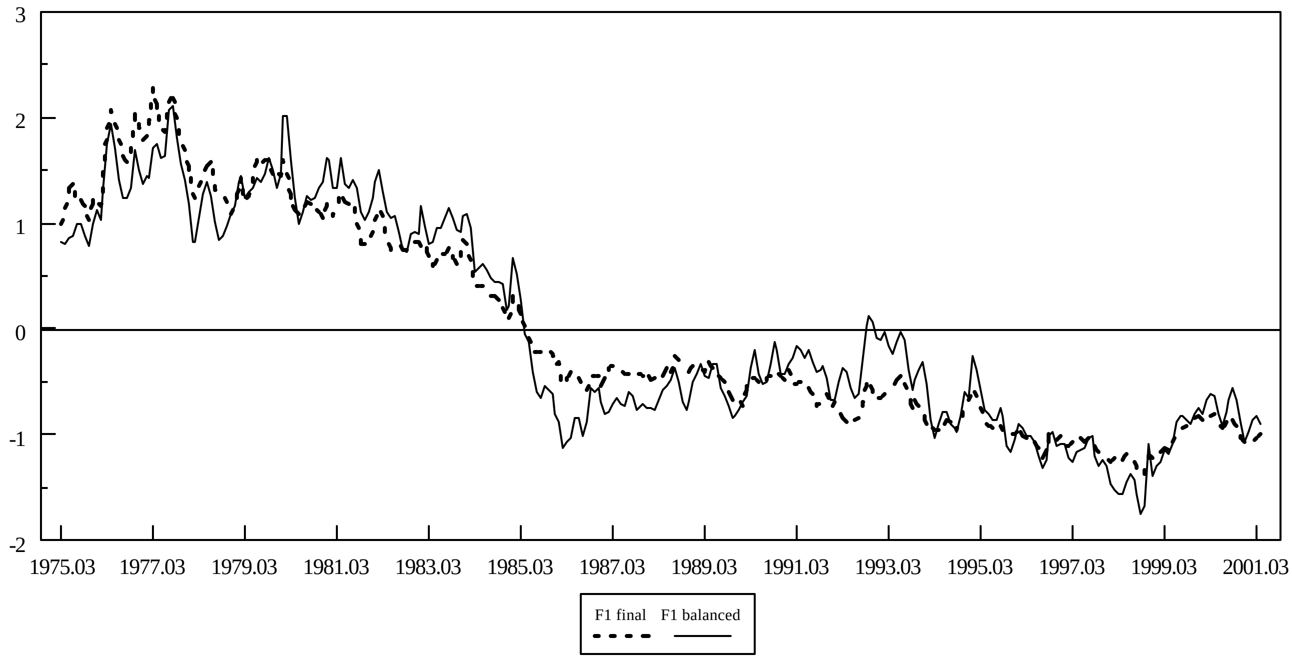
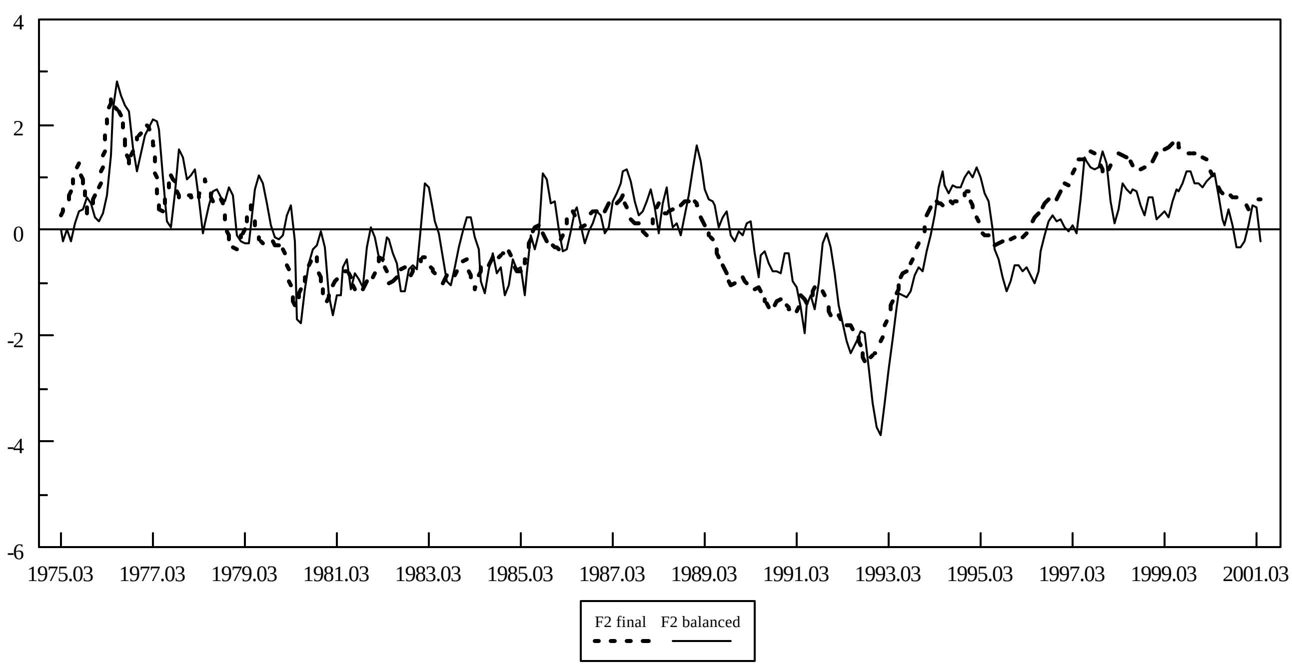
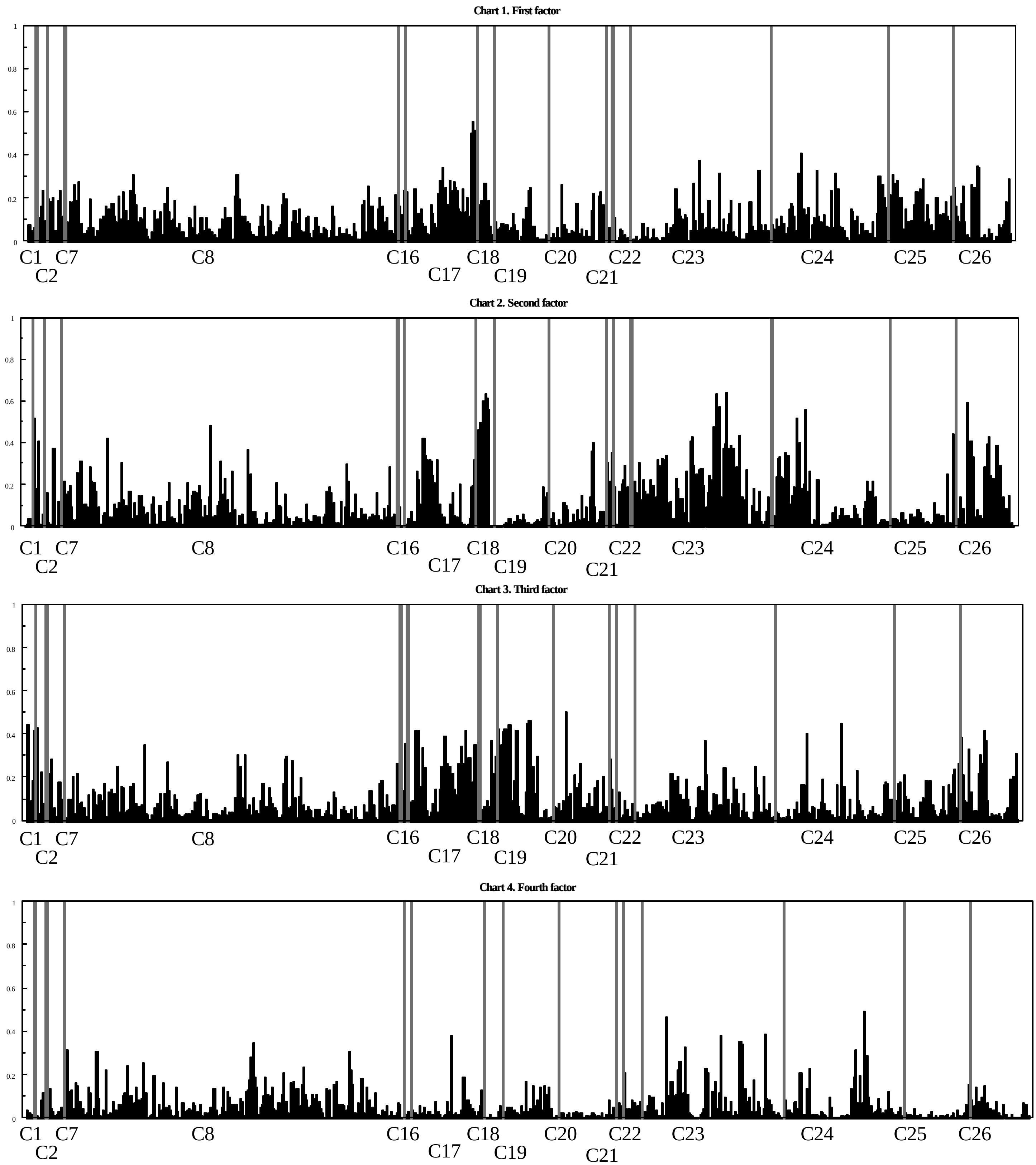


Chart 2. Second factor from balanced and final panels



Note. Figure 2 shows the first (Chart 1) and second (Chart 2) factor of the diffusion indexes model estimated over the sample period 1975.03-2001.04. Balanced (final) factors refers to the estimated factors using the 197 balanced series (1133 series of the entire dataset).

Figure 3. Analysis of main factors



Note. Figure 3 presents the correlations of factors 1 to 4 (Charts 1 to 4) and the Spanish Statistical Bulletin variables, grouped in chapters. Factors are extracted from the final panel that includes 1133 monthly series from 1975.03 to 2001.04.

Figure 4. First factor as nominal indicator

Chart 1. First factor and CPI

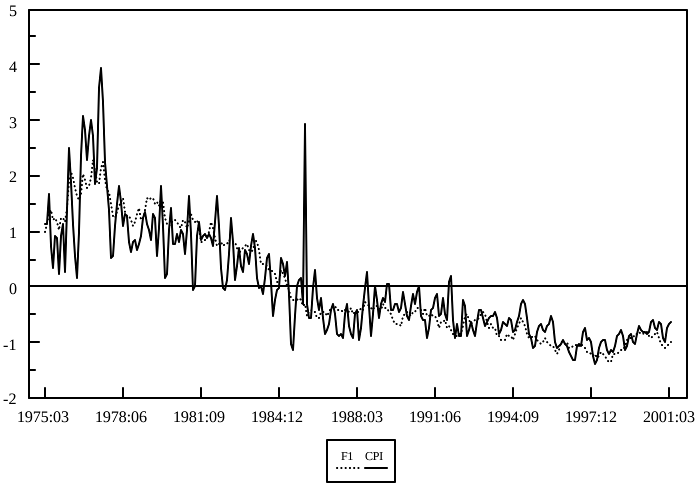


Chart 2. First factor and IPRI

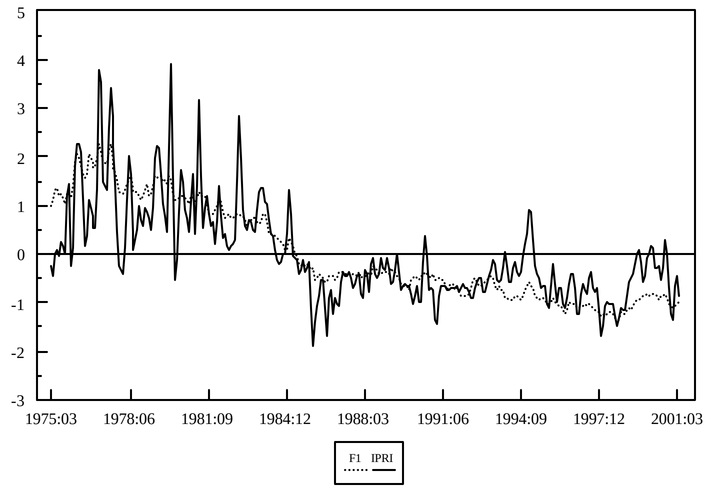


Chart 3. First factor and GDPD

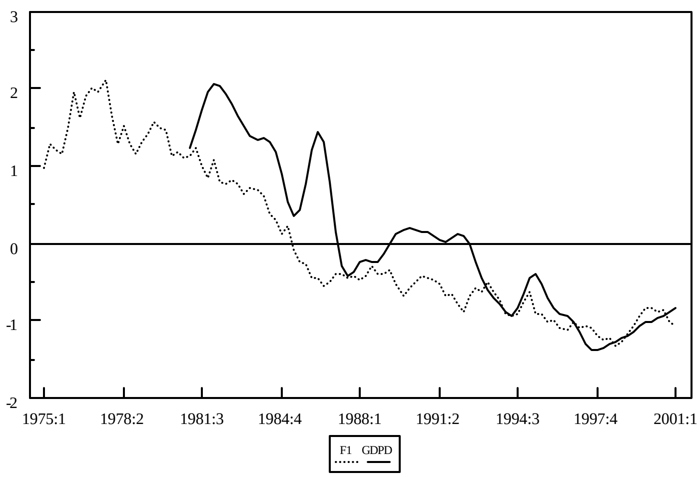


Chart 4. First factor and HCPI

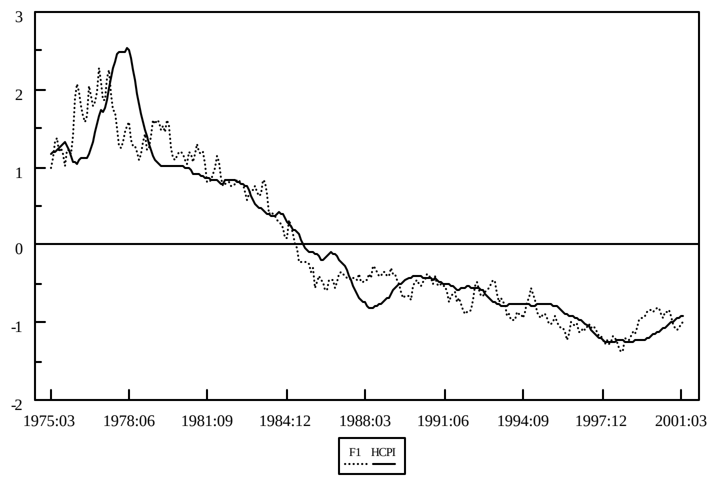


Chart 5. First factor and euro-HCPI

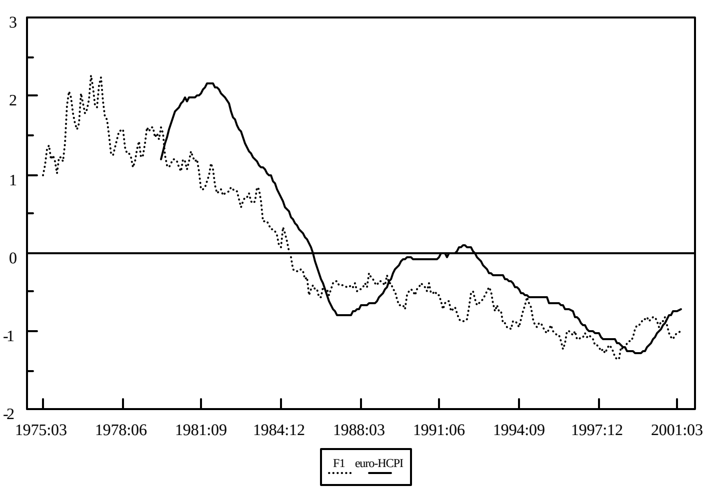


Chart 6. First factor and AHM

Note. F1 refers to our first factor (sample size 1975.03-2001.04). CPI, IPRI, GDPD, HCPI, and Euro-HCPI refer to the rate of growth of consumer price index, industrial prices, GDP deflator, harmonized consumer price index, and Euro-area consumer price index respectively. AHM refers to the first factor of Angelini et al. (2001b). To facilitate comparisions, all series but AHM have been normalized to have zero mean and unit variance. To compare our monthly factor with quarterly series, we take averages within the corresponding quarter. Inflation rates are based on consumer price index and industrial prices, and have been computed on the trend-cycle component of the original series.

Figure 5. Second factor as real indicator

Chart 1. Second factor and GDP

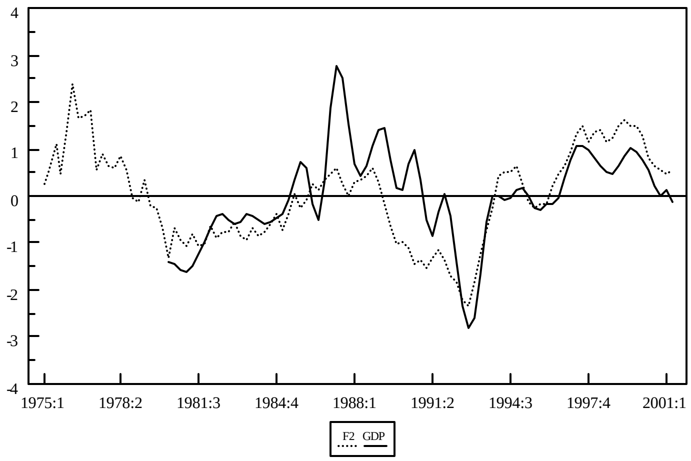


Chart 2. Second factor and U

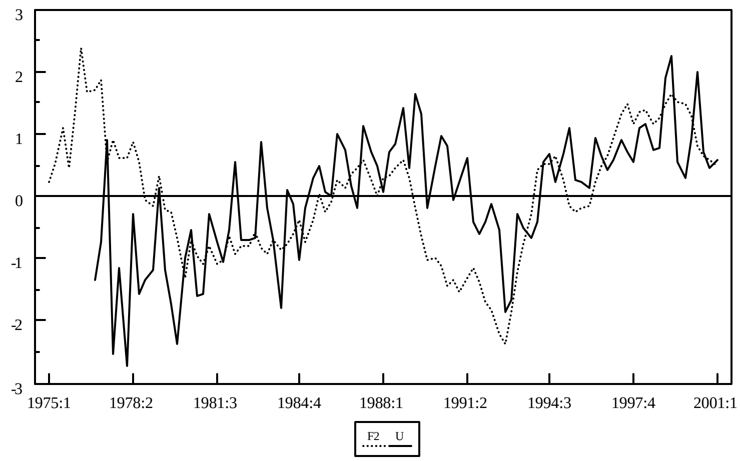


Chart 3. Second factor and SAI

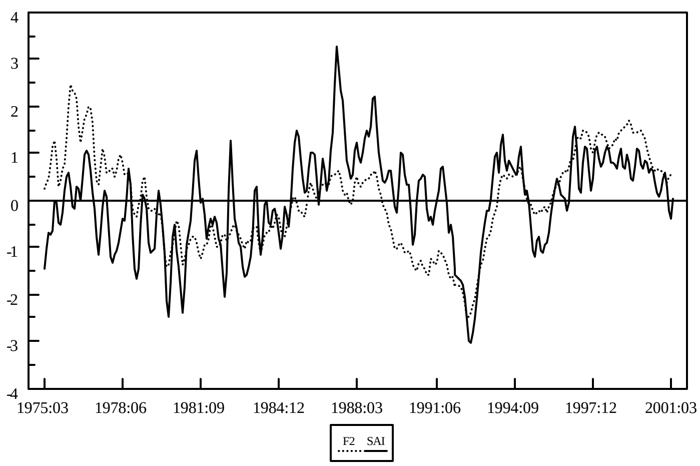


Chart 4. Second factor and INE

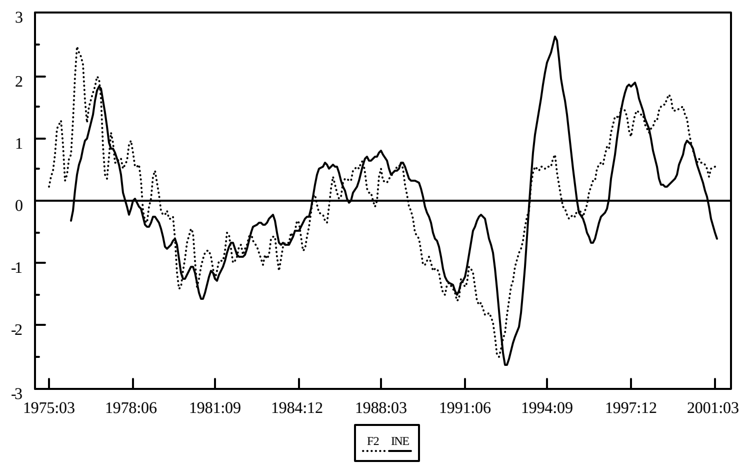


Chart 5. Second factor and EuroCoin

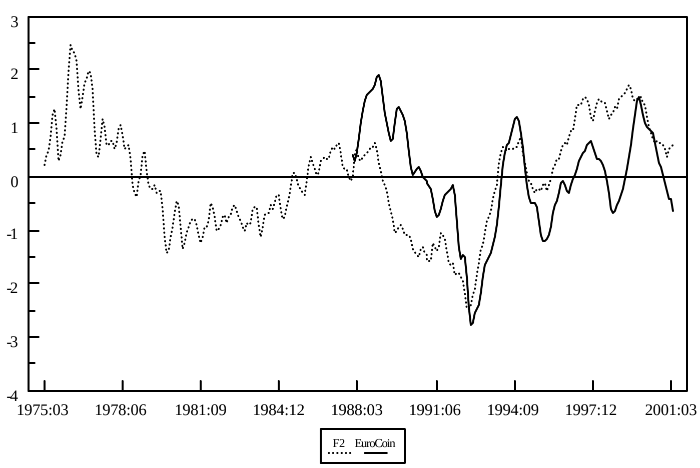
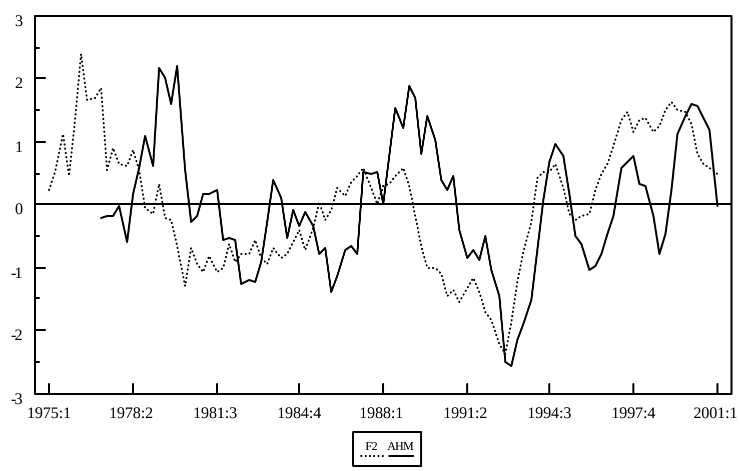


Chart 6. Second factor and AHM



Note. F2 refers to our second factor (sample size 1975.03-2001.04). GDP and U refer to the GDP growth rate and (minus) unemployment growth rate. SAI, INE, EuroCoin and AHM refer to the synthetic activity indicator, coincident indicator, Euro-area coincident indicator and the second factor of Angelini et al. (2001b) respectively. To facilitate comparisions, all series but SAI and AHM have been normalized to have zero mean and unit variance. To compare our monthly factor with quarterly series, we take averages within the corresponding quarter.

Figure 6. Dynamic cross-correlations between the second factor (F2) and other business cycle measures (X). Corr(X(t), F2(t+k))

Chart 1. Second factor and GDP

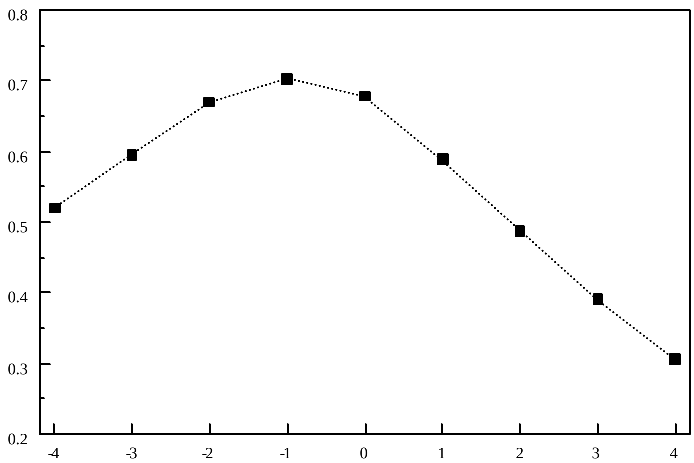


Chart 2. Second factor and U

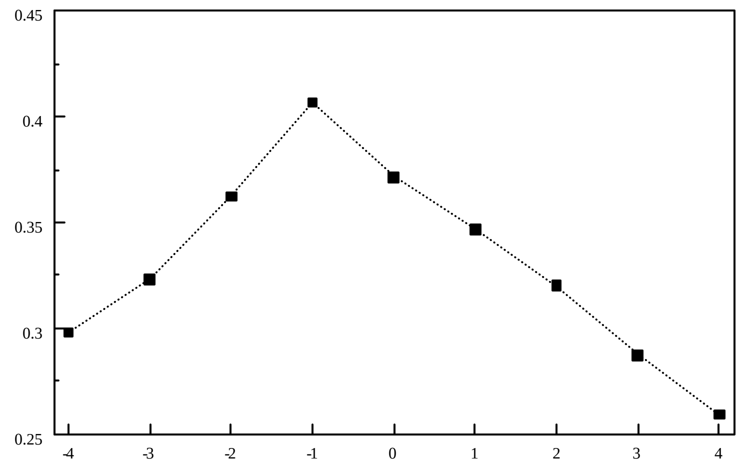


Chart 3. Second factor and SAI

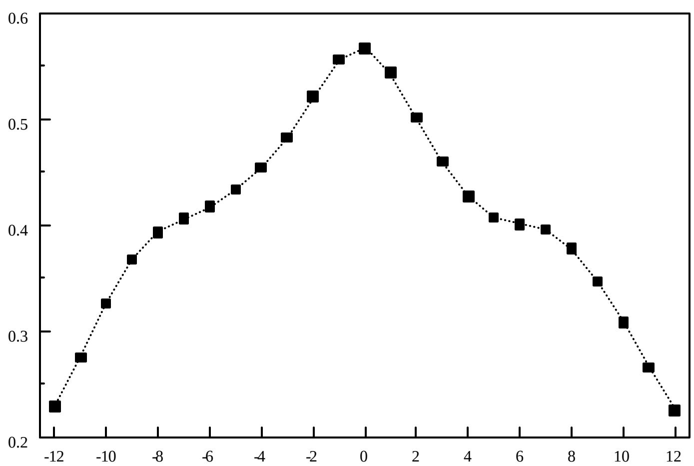


Chart 4. Second factor and INE

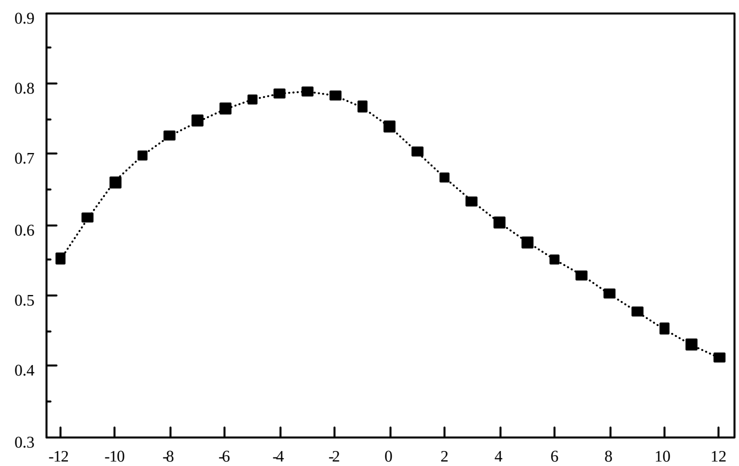


Chart 5. Second factor and EuroCoin

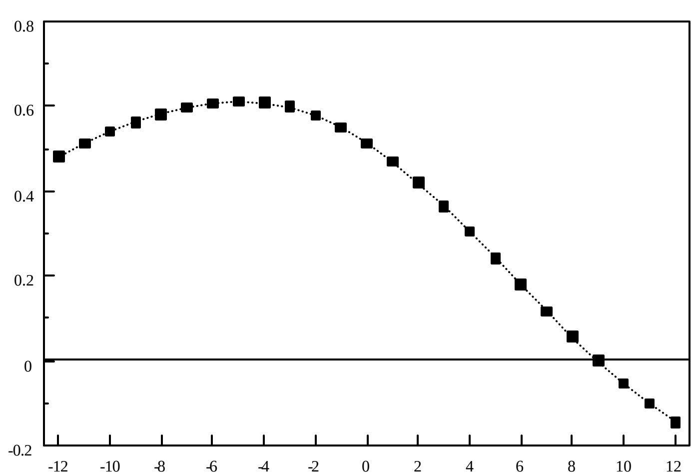
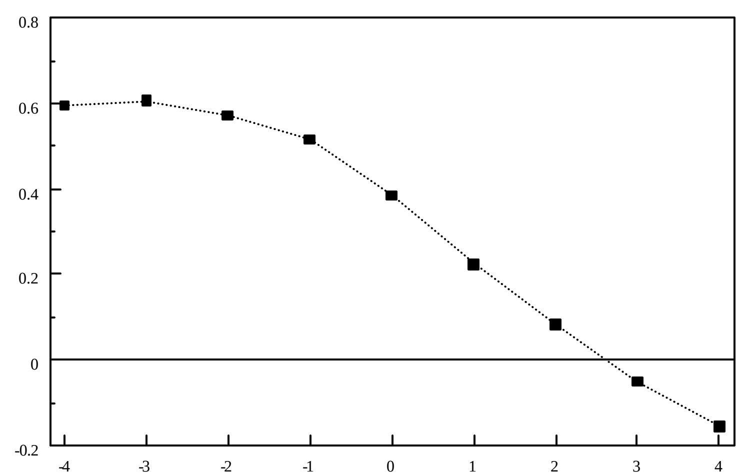


Chart 6. Second factor and AHM



Note. These charts show the cross correlations between the second factor (F2) and the business cycle measures defined in Figure 5. That is, each chart plots Corr(X(t), F2(t+k)), where k goes from -4 to 4 for quarterly series and from -12 to 12 for monthly series.

Figure 7. Business-cycle analysis.

Chart 1. Intercept estimates

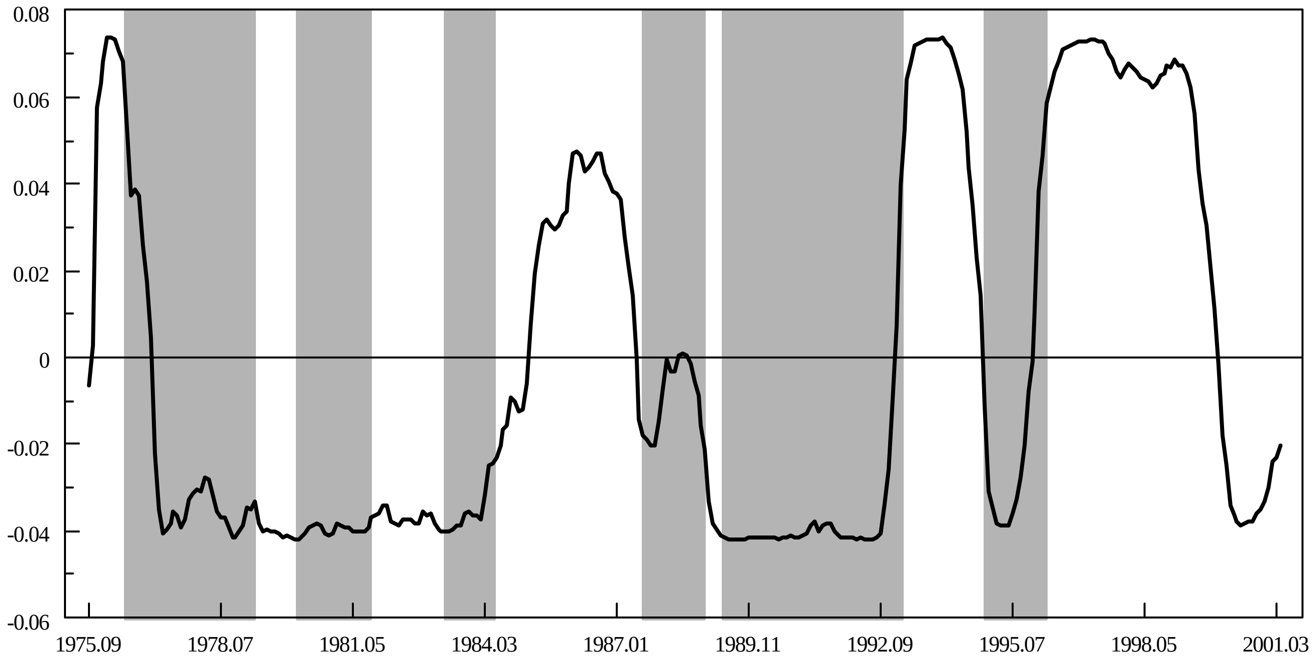
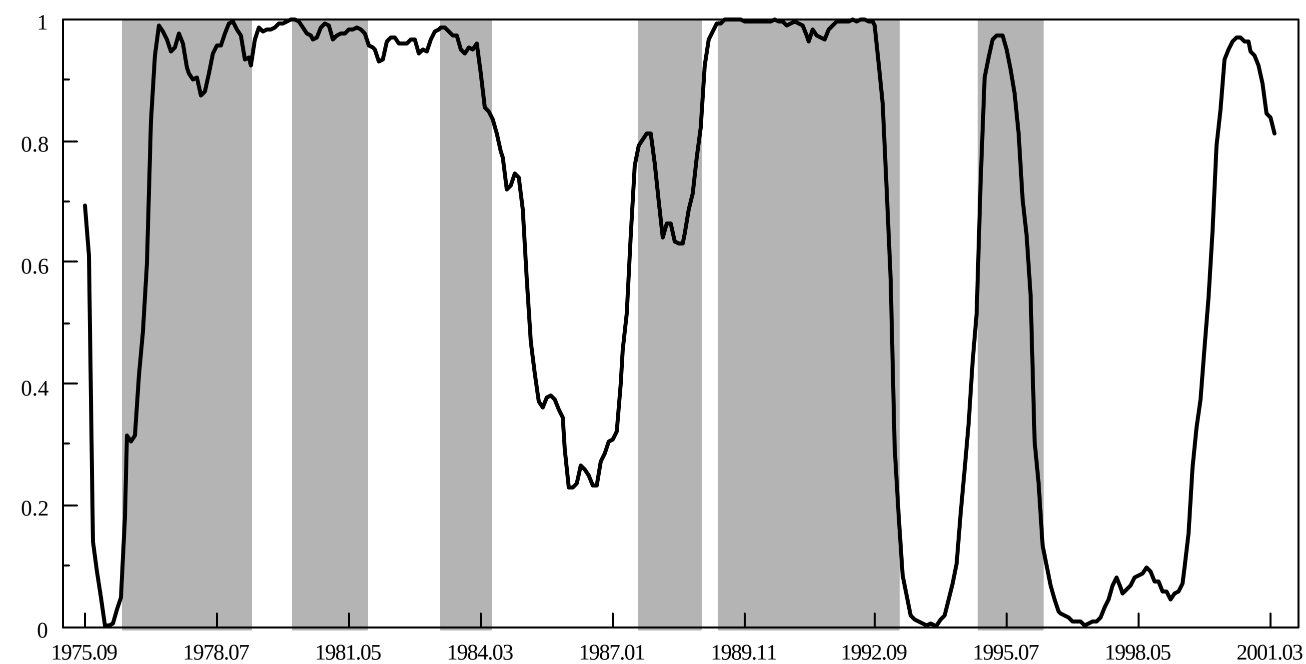


Chart 2. Smoothed probability of state 2



Note. Chart 1 shows the weighted averaged intercept of the Markov switching model for the real activity factor where the weights are the smoothed probabilities. Chart 2 plots the smoothed probabilities of state 2 estimated from that model. Shaded areas refer to the recessionary periods described in Bengoechea (2000). The effective sample is 1975.09-2001.04.

Appendix: Data description

This appendix list the series used to extract the factors. The series has the format PPccaaoo_m_n that should be readed as follows:

PP is the publication code, BE for statistic bulletin.

cc is the chapter with two digits (example: 01 for chapter one)

aa is the table with two digits (example: 01 for table one)

oo is the column with two digits (example: 01 for column one)

m indicates if the series belong to either the unbalanced (u) or the balanced (b) panel

n is the code transformation (1: no transfornation, 2: first difference, 3: second difference, 4: logarithms, 5: first difference of logarithms, 6: second difference of logarithms)

For example, the series BE011302_u_5 is issued in the Statistic Bulletin, in chapter 1, sheet 13 and appears in column 2. This series belongs to the unbalanced panel. We use the stationary difference of the logarithm.

BE011302_u_5	BE170206_u_5	BE170604_b_5	BE190309_b_5	BE200501_u_5	BE222211_u_5
BE011303_u_5	BE170207_u_5	BE170605_b_5	BE190310_b_5	BE200503_u_5	BE222212_u_5
BE011304_u_5	BE170208_u_5	BE170606_b_5	BE190311_b_5	BE200504_u_5	BE222301_u_5
BE011305_u_5	BE170209_u_5	BE170607_b_5	BE190312_b_5	BE200505_u_5	BE222501_u_5
BE011306_u_5	BE170210_u_5	BE170608_b_5	BE190313_u_5	BE200506_u_5	BE222502_u_5
BE011307_u_5	BE170211_u_5	BE170701_b_5	BE190314_b_5	BE200507_u_5	BE222503_u_5
BE011308_u_5	BE170212_u_5	BE170702_b_5	BE190315_b_5	BE200508_u_5	BE222504_u_5
BE020701_u_5	BE170213_u_5	BE170703_b_5	BE190316_b_5	BE200509_u_5	BE222505_u_5
BE020702_b_5	BE170214_u_5	BE170704_b_5	BE190317_b_5	BE200510_u_5	BE222506_u_5
BE020902_u_1	BE170215_u_5	BE170705_b_5	BE190318_b_5	BE200511_u_5	BE222507_u_2
BE020904_u_1	BE170216_u_5	BE170706_b_5	BE190319_b_5	BE200512_u_5	BE222508_u_2
BE020905_u_1	BE170302_u_5	BE170707_b_5	BE190320_b_5	BE200513_u_5	BE222509_u_5
BE020907_b_1	BE170303_u_5	BE170708_b_5	BE190321_b_5	BE200514_u_5	BE222510_u_5
BE021001_b_5	BE170304_u_5	BE180101_b_1	BE190322_b_5	BE200515_u_5	BE222511_u_5
BE011301_u_5	BE170305_u_5	BE180102_u_1	BE190401_u_5	BE200601_u_5	BE222512_u_5
BE021002_b_5	BE170306_u_5	BE180103_b_1	BE190402_b_5	BE200602_u_2	BE230101_b_5
BE021003_b_5	BE170307_u_5	BE180104_u_1	BE190403_b_5	BE200603_u_5	BE230102_b_5
BE021004_b_5	BE170308_u_5	BE180202_u_1	BE190404_b_5	BE200604_u_5	BE230103_b_5
BE021008_u_5	BE170309_u_5	BE180203_u_1	BE190405_b_5	BE200605_u_5	BE230104_b_5
BE021009_u_5	BE170310_u_5	BE180205_u_1	BE190406_b_5	BE200606_u_5	BE230105_b_5
BE071401_b_5	BE170311_u_5	BE180301_u_1	BE190407_b_5	BE200607_u_5	BE230106_b_5
BE071402_b_5	BE170312_u_5	BE180302_u_1	BE190408_b_5	BE200608_u_5	BE230107_b_5
BE071405_u_5	BE170313_u_5	BE180306_u_1	BE190409_b_5	BE200609_u_5	BE230108_b_5
BE071406_u_5	BE170314_u_5	BE180308_u_1	BE190410_u_5	BE200610_u_5	BE230109_b_5
BE071407_u_5	BE170315_u_5	BE180310_u_1	BE190411_b_5	BE200611_u_5	BE230110_b_5
BE071408_u_5	BE170316_u_5	BE180312_u_1	BE190501_b_5	BE200612_u_5	BE230111_b_5
BE071409_b_5	BE170403_u_5	BE180402_u_1	BE190502_b_5	BE200613_u_2	BE230112_b_5
BE071410_u_5	BE170404_u_5	BE180404_u_1	BE190504_b_5	BE200614_u_2	BE230113_b_5
BE071413_b_5	BE170406_u_5	BE180406_u_1	BE190505_u_5	BE200615_u_5	BE230114_b_5
BE071507_b_5	BE170407_u_5	BE180408_u_1	BE190506_b_5	BE200616_u_5	BE230115_b_5
BE071508_u_5	BE170408_u_5	BE180410_b_1	BE190507_b_5	BE200701_b_5	BE230116_b_5
BE071509_b_5	BE170409_u_5	BE180412_u_1	BE190508_b_5	BE200702_b_5	BE230202_b_5
BE071510_u_5	BE170410_u_5	BE180413_u_1	BE190509_u_5	BE200703_u_2	BE230203_b_5
BE071511_b_5	BE170411_u_5	BE190101_u_5	BE190510_b_5	BE200704_u_5	BE230204_b_5
BE071512_u_5	BE170412_u_5	BE190102_u_5	BE190511_b_5	BE200705_u_5	BE230205_b_5
BE071513_b_5	BE170413_u_5	BE190103_u_5	BE190603_u_5	BE200706_u_2	BE230207_b_5
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