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Choosing a dynamic common factor as a coincident index

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ABSTRACT

A methodology to compute a coincident index is presented. The procedure is based on the common factors of a set of indicator variables and a device that is termed coincident profile. Applications in economics and finance are included.

1. Introduction

In certain disciplinary fields, as for example, economics, finance, and climatology, it is usually necessary to design indexes for tracking the dynamic evolution of an underlying latent stochastic process, which represents the state of nature of a dynamic system. In this way, we have adequate information about, for example, the so-called *state* of the economy of a country or of its global *business cycle* (in Burns and Mitchell's (1946) philosophy). Three kinds of indexes are frequently considered: lagging, coincident and leading. In this paper, our goal is on coincident indexes, which are constructed using indicator variables that move contemporaneously with the *state* of interest.

From the point of view of statistics, the index (as a time series) is considered an estimate of the latent stochastic process that represents the state of the system. At present, there is a lot of literature on the topic of designing coincident indexes. The procedures range from the heuristic weighted averages of the observed data up to model-based time series approaches. In the first scenario, the weights for the variables are chosen in an ad-hoc way without taking into account, at least, the time-series correlation structure. Thus, optimality properties of the index, as an estimate, are unknown. In the second case, some advances have been developed. Among others, and in the economics context, we can quote the model-based econometric approach of Stock and Watson (1989, 1991) and ex-post and ex-ante prediction procedure of Nieto (2004). In the first paper, the key point is the definition of the state of the economy as a latent stochastic process. Then, they assume that coincident observable variables emerge from this process, via a linear relationship. Optimal prediction (in the minimum-mean-square error sense) of this latent process, based on the observed variables, is then considered as the index. When the observed time series are non-stationary, if we assume only one common factor (as it is usually done), this implies that the indicator variables or processes are cointegrated with rank $m-1$, being m the number of variables. When m is large, this implied condition from the model is very difficult to be fulfilled in practice. In Nieto (2004), the state of the economy is represented by a latent process that is not observable at high-frequency time periods, usually the Gross National Product (GNP). Then,

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this is optimally predicted using indicator variables at low-frequency time periods and a contemporaneously high frequency preliminary observable process, which is related to the latent one. The predicted (or estimated) process is then considered as a coincident index. The main disadvantage of this procedure is the waiting time for the data at the lower frequency. This precludes the use of this procedure for tracking the state of a dynamic system in real time (or on line). Additionally, the higher frequency coincident index might represent the specific lower frequency indicator at a higher frequency, but we would like to have a richer or more informative index that represents that state of the system and does not resemble so much a specific indicator.

In order to fix the drawbacks quoted above, but motivated by the only-one common factor model of Stock and Watson (1989, 1991), we propose a new conceptual approach. The idea is to estimate optimally the common factors of a multivariate process that is conformed by indicator variables of the state of the system and then, to chose one of them as the coincident index. Common factor models have received considerable attention (see, for instance, the surveys by Bai and Ng (2008), and Stock and Watson (2011)), although most of the research has been conducted assuming stationarity. Under this scenario, spectral methods (see, among others, Altissimo et al. (2010), Azevedo et al. (2006)) and principal components using large data sets (see, for instance, Stock and Watson (2002), and Forni et al. (2000, 2005)) have been entertained. In order to achieve stationarity, the series are prefiltered in a univariate fashion taking first or second differences as required. However, the Nobel prize Christopher Sims (Sims, 2012) casts some doubts about this practice, pointing out that by differencing individual series when they are non-stationary and cointegrated, we are throwing away vast amounts of information and may distort inference.

Peña and Poncela (2006) introduce the generalized lagged covariance matrices to identify non-stationary common factors. The same tool is extended by Lam and Yao (2012) for dynamic factor models with a large number of observed time series. Under the common-factors framework, another novelty of our paper is that it is able to deal with non-stationary data. Economic time series are usually non-stationary and cointegrated, so they should be modeled through non-stationary factor models.[1]

To choose one estimated common factor as the coincident index, we shall follow Banerji's (1999) lead profile procedure. This is a tool to obtain leading indexes. Our goal is to define a *coincident* profile. The paper is organized as follows. In Section 2 we briefly describe the dynamic non-stationary common factor methodology and the lead-profile approach. Section 3 presents the proposed common-factor based methodology for designing a coincident index. In Section 4 we apply our methodology to the Colombian economy and the Colombian stock exchange. Section 5 concludes.

2. Theoretical background

2.1. Common factor model

Our paper is based on Peña and Poncela's (2006) approach for obtaining dynamic common factors. However, an alternative procedure that might be considered is that of Lam and Yao (2012), which is very useful in the case of many observable variables. The basic model is given by the equation

$$\mathbf{y}_t = \mathbf{P}\mathbf{f}_t + \mathbf{e}_t, \tag{1}$$

where $\{\mathbf{y}_t\}$ is an m-dimensional observable stochastic process, $\{\mathbf{f}_t\}$ is an r-dimensional latent stochastic process whose components are termed the common factors, $\{\mathbf{e}_t\}$ is an m-dimensional zero-mean Gaussian stationary process with diagonal variance Σ_e, and $\mathbf{P}$ is the so-called factor loading matrix. Here $r < m$. It is assumed additionally that $\{\mathbf{f}_t\}$ obeys the VARMA(p, q) model,

$$\mathbf{\Phi}(B)\mathbf{f}_t = \mathbf{d} + \mathbf{\Theta}(B)\mathbf{a}_t, \tag{2}$$

where $\mathbf{\Phi}(B) = \mathbf{I} - \mathbf{\Phi}B - \cdots - \mathbf{\Phi}_{\boldsymbol{p}}B^{\boldsymbol{p}}$ and $\mathbf{\Theta}(B) = \mathbf{I} - \mathbf{\Theta}B - \cdots - \mathbf{\Theta}_{\boldsymbol{q}}B^{\boldsymbol{q}}$ are polynomial matrices in the lag operator B, such that the roots of the determinant equation $|\mathbf{\Phi}(B)| = \mathbf{0}$ are outside or on the unit circle and the roots of $|\mathbf{\Theta}(B)| = \mathbf{0}$ are outside the unit circle. Furthermore, $\mathbf{d}$ is an $m \times 1$ constant vector and $\{\mathbf{a}_t\}$ is a zero-mean Gaussian multivariate process with variance $\mathbf{\Sigma}_{\boldsymbol{a}}$, which is of full rank. The two processes $\{\mathbf{e}_t\}$ and $\{\mathbf{a}_t\}$ are assumed to be independent. It is important to remark here that the components of $\{\mathbf{f}_t\}$, as stochastic processes, can be either non-stationary or stationary. Each element of the idiosyncratic noise follows a univariate autoregressive process. Therefore, we allow for serial but not cross-correlation in $\{\mathbf{e}_t\}$.

Inference about the number of factors and their type is made through the so-called sample generalized covariance (SGCV) matrices, which are defined by

$$\mathbf{C}_y(k) = \frac{1}{T^{2d+1}} \sum_{t=k+1}^{T} (\mathbf{y}_{t-k} - \overline{\mathbf{y}})(\mathbf{y}_t - \overline{\mathbf{y}})'; \quad k = 0, 1, \ldots, \tag{3}$$

[1] See Escribano and Peña (1994), who show that if several time series are cointegrated, there are non-stationary common factors among them.

where $\bar{\mathbf{y}} = \frac{1}{T}\sum_{t=1}^{T}\mathbf{y}_t$, and by the canonical correlation matrices

$$\widehat{M}_1(k) = \left[\sum_{t=k+1}^{T}\mathbf{y}_t\mathbf{y}_t'\right]^{-1}\sum_{t=k+1}^{T}\mathbf{y}_t\mathbf{y}_{t-k}'\left[\sum_{t=k+1}^{T}\mathbf{y}_{t-k}\mathbf{y}_{t-k}'\right]^{-1}\sum_{t=k+1}^{T}(\mathbf{y}_{t-k}\mathbf{y}_t'), \tag{4}$$

with $k = 1, 2, \ldots$. Peña and Poncela (2006) developed a statistical test to detect the total number (non-stationary/stationary) of common factors and with the help of the SGCV matrices, the number of non-stationary common factors can be specified. Writing the model given in Eqs. (1) and (2) in the state space form, we can estimate it by maximum likelihood, using the Kalman-filter-based fixed point smoother to extract the common factors.

2.2. The leading profile

Banerji (1999) proposes a nonparametric methodology for evaluating the leading capability of a proposed leading index, based on Fisher's randomization test for matching pairs (see Lehmann and Romano (2005)). The idea is the following: suppose we have a proposed leading index and a reference cycle and observe Q turning points in each of them, so that we have Q pairs of the form either peak–peak or trough–trough. For easiness, let us consider peak–peak pairs. Then, the interest is to check if the observed peaks of the proposed index *anticipate* those observed in the reference cycle. Thus, the statistical hypotheses $H_0 : \sum d_i = 0$ v.s. $H_1 : \sum d_i > 0$ are considered, where d_i is the observed difference (months, quarters, etc.) between the peaks of the ith pair ($i = 1, \ldots, Q$).

To test the null hypothesis against the proposed alternative, we obtain the 2^Q possible sequences of length Q of the signs $\pm$ and assign these sign patterns to the absolute values of $d_1, \ldots, d_Q$. Then, we compute the sum of each signed sequence and count how many of these sums are greater than or equal to the observed sum. Suppose there are R of such sums, then the p-value of the test becomes $(R/2^Q)100\%$. Now, if the decision is to reject H_0 in favor of H_1, the question is, how many time periods does the proposed leading index lead the reference series? To answer this question, we consider the sequence of null hypotheses $H_0^{(l)} : \sum(d_i - l) = 0$, where $l = 1, \ldots, K$ for some K, and take up, as the (estimated) leading period, the value l for which both the corresponding null hypothesis is not rejected and its p-value is the highest.

3. The proposed methodology

3.1. A coincident profile

In this paper, our concern is on a coincident index instead of a leading one and our interest is in (i) no rejecting $H_0 : \sum d_i = 0$ and (ii) extending Banerji's (1999) idea in the sense of including the differences between troughs. Additionally, we set $H_1 : \sum d_i \neq 0$ as the alternative hypothesis.

In this way, we are led to consider a randomization test with a two-side alternative as those of Welch and Gutiérrez (1988). The strategy for doing the test is as follows: let D_0 be the observed total sum of differences (peaks and troughs) and $D_j(l) = \sum(d_i^{(j)} - l)$ (over peaks and troughs), where $d_i^{(j)}$ is the ith difference of the jth sequence, with $j = 1, 2, \ldots, 2^Q$; $l = 0, \pm 1, \ldots, \pm K$ and K is some positive integer; then, the p-values are given by

$$p_l = \frac{\#\{D_j(l) : |D_j(l)| \geq |D_0|;\ j = 1, 2, \ldots, 2^Q\}}{2^Q}, \tag{5}$$

where $\#\{\cdot\}$ denotes the cardinal of the set $\{\cdot\}$.

Now, we design a bar chart where the chosen values of l are located on the abscissa and the corresponding p-values on the ordinate. We expect that p_0 is both greater than a given significance level and greater than p_l for all $l \neq 0$ and thus, we consider the entertained index as a *coincident* index. We call this graph a *coincident profile* and it is an extension of Banerji's lead profile. If there is more than one competing index, we would prefer that for which the corresponding p_0 is the highest among all the competing coincident profiles.

3.2. Using common factors

Conceptually, common factors of an observable multivariate stochastic process, which is composed of univariate processes that are coincident for the system state under study, can be considered potential coincident indexes. Of course, if there is only one, this factor can be interpreted as a coincident index and this situation is in line with Stock and Watson's (1989) philosophy. When there is more than one common factor, it is desirable to decide which one is more adequate to be considered as the coincident index. We propose to use the coincident profile in order to make that decision. To do so we need to consider an alternative proxy for the state of nature of the dynamic system. There are several reasons for not using this alternative proxy as our index. First, it may be published with a long delay and, by the time we can use it, it is too late. So the first reason is timing. The second reason is to capture more accurately the state of nature of the precise phenomenon that we are analyzing. Alternative proxies might be gross approximations for the state of nature of the dynamic system.

As it will be illustrated in the empirical applications, the idea is (i) to estimate the common factors, (ii) to consider an alternative proxy or preliminary estimate of the state of nature of the dynamic system, and (iii) to obtain the coincident profiles between each one of the estimated common factors and the alternative proxy.

Essentially, our proposed *step-by-step procedure* is the following:

STAGE 1. *Adjust the time series*. Deseasonalize eventual seasonal time series, correct for outliers if any, and adjust for scale if necessary.

STAGE 2. *Estimate common factors*. Following Peña and Poncela's (2006) procedure, find the common factors estimates. Obviously, if desired, Lam and Yao's (2012) methodology could be used alternatively to get this goal. If after an initial fitting of a factor model, it is detected that the intrinsic noise is colored, specify an autoregressive stationary model for each univariate intrinsic noise in order to explain the serial correlation and repeat the model estimation.

STAGE 3. *Choose a common factor*. Using the preliminary estimate of the system, other than the observed coincident variables, obtain the coincident profile for each common factor. As the candidate coincident index, choose the common factor for which its p-value at $l = 0$ is both greater than a pre-specified significance level and the highest among all the coincident profiles.

STAGE 4. *Set the index base*. Put the time base for which the chosen factor in Stage 3 is an index and analyze its main properties for the field under consideration, i.e. economics, finance, climate, etc.

Remark. It is important to note here the following practical fact. When the number of turning points in the two time series that are being compared is not the same, we recommend choosing the pairs of turning points, i.e. peak–peak and trough–trough, in the following way: take the first peak of the first time series, then compute the chronological difference with each one of the peaks of the second time series and choose the peak in this time series that leaves the smallest algebraic difference. Now, consider the second peak of the first time series and compute the differences with all the peaks of the second one but the peaks that precedes the one chosen in the previous step. Take from the second time series that for which the difference is the smallest. This procedure for pairing peaks is repeated until either all the peaks in the first time series have been considered or all the peaks in the second series have been exhausted. Finally, do the same task for pairing troughs. This procedure is used in the real-data applications below.

4. Real data applications

In this section we apply our method in the Colombian economic and financial fields.

4.1. Macroeconomic sector

Nowadays, there is not a monthly coincident index for the Colombian economy. However, for the sample period January, 1980, to December, 2005, Melo et al. (2001) designed a monthly index, which was based on Stock and Watson's (1989) philosophy. Then, working on Melo et al.'s (2001) model and using the Bayesian approach for estimating the model parameters and the unique common factor, as described by Kim and Nelson (1999), Castillo and Nieto (2008) revisited the computation of the index obtaining improvements in the precision of the model parameter estimates. In those works, the following macroeconomic variables were used: cement production (CEM), industrial production index excluding coffee threshing (IPR), index of employment for unskilled workers (EMP), currency in circulation in real terms (EFE), demand of energy and gas (ENE), total imports excluding capital and durable goods (IMP), loan portfolio of the financial system (CAR), current economic conditions (FP1), and number of pending orders from the industry (FP6).

For comparison purposes, we use the same sample period to obtain an index via our approach. Using Nieto's (2004) procedure, we obtain an initial estimate of the Colombian monthly GDP and, thus, this time series will be the initial estimate of the economic system. We obtained the following results.

STAGE 1. All the time series were adjusted for seasonality and for interventions and outliers using the TSW package of Caporello and Maravall (2003). Also, we made an adjustment for scale using a "standardization" of each time series. That is to say, with n as the sample size and $s_i^2 = (1/n)\sum_{j=1}^{n}(y_{ij} - \bar{y}_i)^2$, where y_{ij} denotes the jth observation of variable Y_i and $\bar{y}_i$ is the sample mean of the data for variable i, $i = 1, \ldots, 9$, we put as new data $x_{ij} = (y_{ij} - \bar{y}_i)/s_i$, $j = 1, \ldots, n$, for the ith variable. The transformed time series are plotted in Fig. 1.

STAGE 2. Using the transformed data set, we detected 3 common factors. In order to estimate them, we specify a random-walk model for each factor because the Augmented Dickey–Fuller test for the null hypothesis of a unit root signaled that all the series are integrated of order one, $I(1)$, and a random walk for the common factors, which is also $I(1)$, is able to capture the non-stationary behavior of the observed series. For the intrinsic noises we specify AR(2) models.[2] The estimated common factors and monthly GDP (without standardizing) are plotted in Fig. 2. We note here that the full sample was used to estimate the common factors (and this will also apply to the second example below). In future research, we will address the issue of estimating the common factors in a recursive way, that is, estimating the factors for the time we have new observations of the indicator variables and preserving the previous estimates.

[2] The full set of parameter estimates can be provided by the authors upon request.

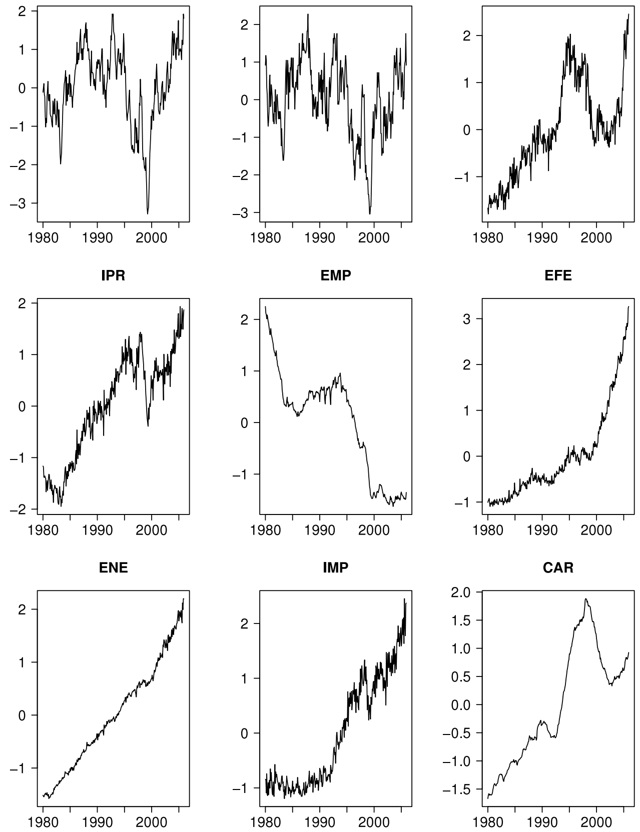

Fig. 1. Adjusted macroeconomic time series.

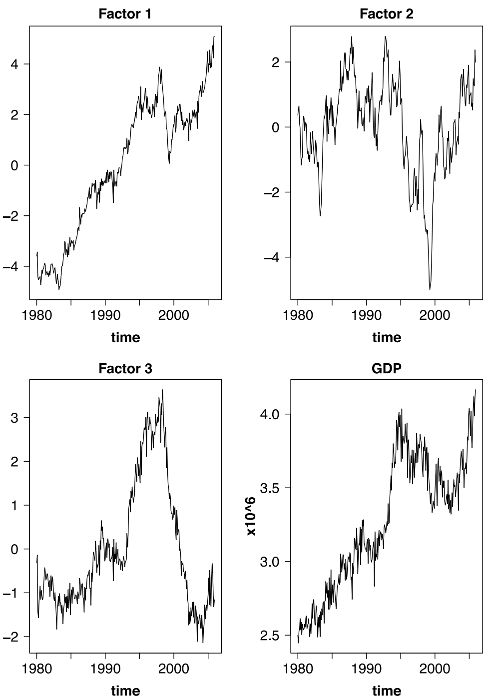

Fig. 2. The three predicted factors and GDP time series for the Colombian economy.

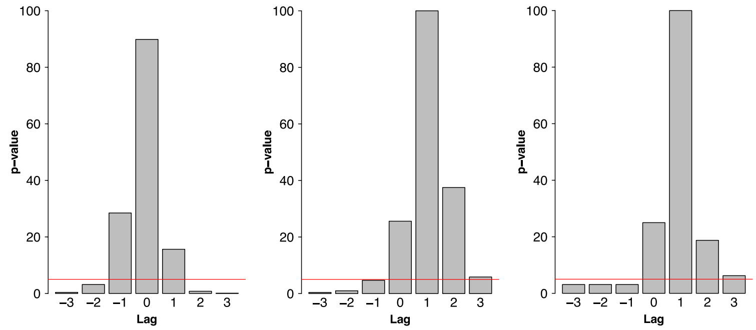

Fig. 3. Coincident profiles for the three common factors. From left to right: factor 1, factor 2, and factor 3.

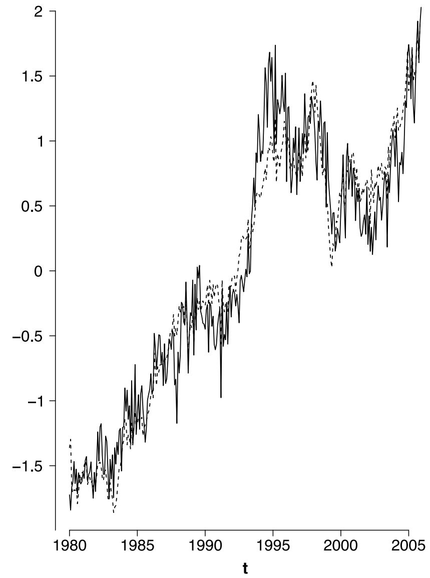

Fig. 4. Proposed coincident index (dashed line) and GDP (solid line).

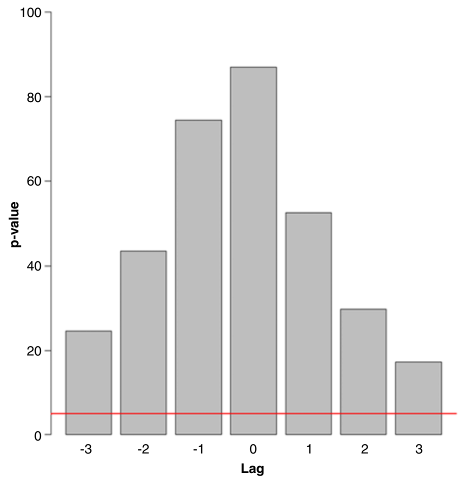

Fig. 5. Coincident profile for Castillo and Nieto's (2008) index.

It is worth noticing that the three common factors have good explanatory power for the observed series. To check this fact, we have regressed each one of the observed series over a constant and the three estimated common factors and we have

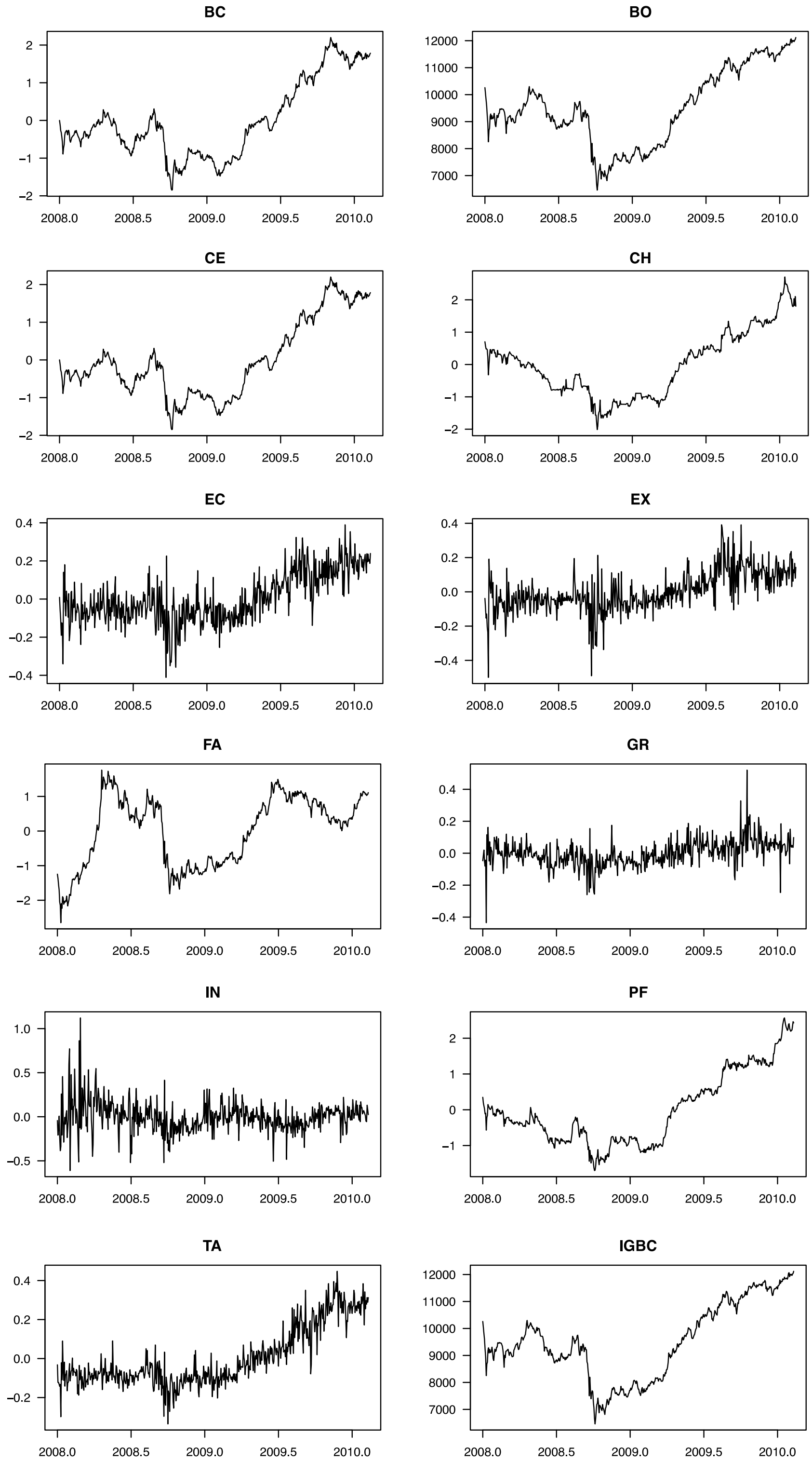

Fig. 6. Time series for the financial example and the IGBC.

obtained the following R^2s (in the variables order quoted above): 0.9801, 0.8412, 0.8953, 0.9987, 0.9062, 0.9630, 0.9379, 0.9901, 0.9086. These results indicate that the common factors explain most of the variability of the observed series.

STAGE 3. Now, we proceed to obtain the 5%-significance-level coincident profile for each estimated common factor. In Fig. 3 we see that the first common factor has the largest p-value at lag zero among all the 3 coincident profiles and its

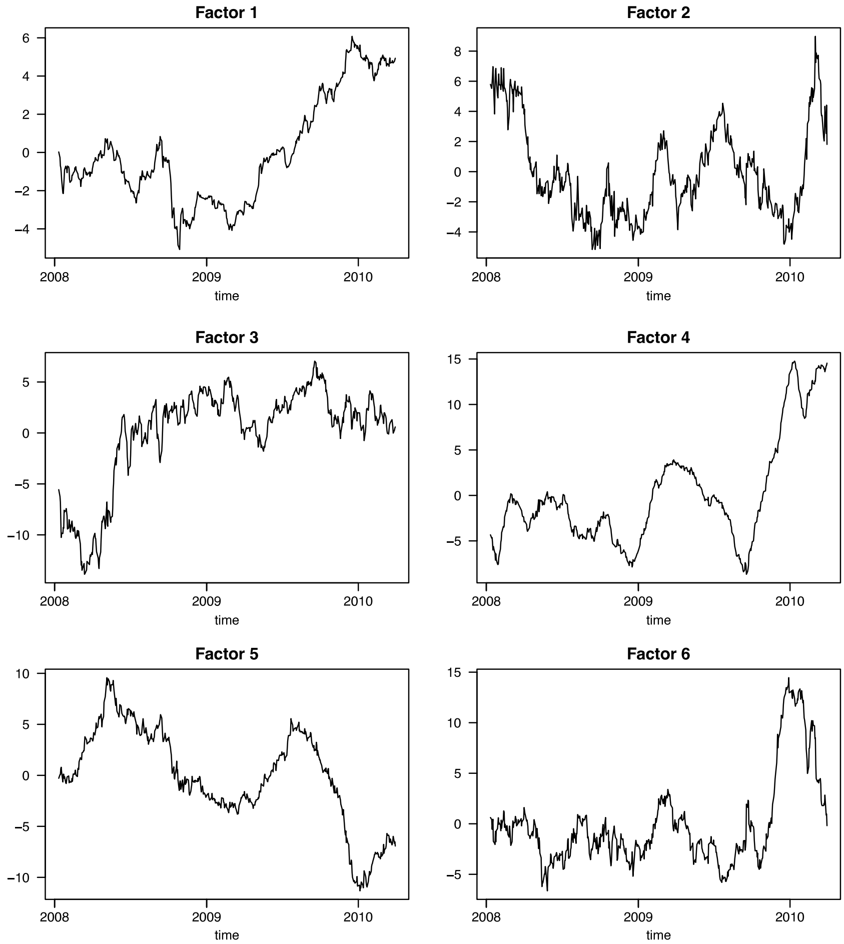

Fig. 7. Common factors in the financial application.

coincident profile is approximately symmetric around 0. Consequently, this factor can be considered as a coincident index for the state of the Colombian economy.

STAGE 4. We set 1980:01 as the basis for the index and this is plotted in Fig. 4 jointly with the standardized monthly GDP. As we can observe there, the proposed index tracks reasonably well the stylized facts of the Colombian economy in the sample period considered. Specifically, its expansions and contractions.

In Fig. 5 we plot the coincident profile for Castillo and Nieto's (2008) index and we observe that, although there is *coincidence*, it is not symmetric around zero and has large p-values at lags $l = \pm 1$, contrary to the facts observed for the first common-factor coincident profile. Because of this result, we consider that our index is an improvement of Castillo and Nieto's (2008) one. We feel that this result is due to the fact that, first, we extract all the common factors and then, we choose the more coincident one. Under Castillo and Nieto's (2008) approach, one common factor is fixed a priori and then this is estimated.

4.2. Financial application

Now, we study the Colombian stock exchange in the sample period January 2, 2008–March 31, 2010. A daily composite index for this market was the General Index of the Colombian Stock Exchange (IGBC for its Spanish acronyms), which was computed with the stocks of 52 financial institutions (banks, factories, investment firms, etc.). However, since November, 2013, this index was not computed anymore and nowadays, there is a new index that is called COLCAP and it is based on the capitalization value of some financial institutions. Because of this situation and for comparison purposes, we maintain the same sample period to obtain a financial index using our procedure. Nevertheless, IGBC will be our preliminary estimate of the state of the Colombian financial system. From the 52 stocks, we choose the following 11: BC (Bank of Colombia), BO (Bank of Bogotá), CE (ARGOS Cement), CH (Chocolate National Factory), EC (Colombia Oil Company), EX (EXITO Stores), FA (Textile Factory), GR (AVAL Financial Group), IN (ARGOS Investments), PF (Bancolombia S.A.-preferred action), TA (Particle board and plywood—furniture and wooden products).

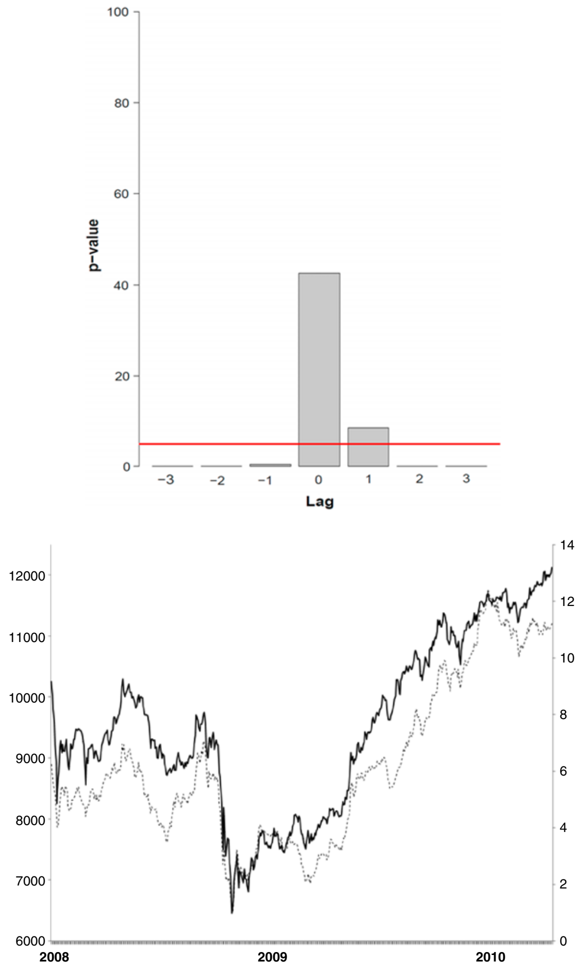

Fig. 8. Coincident profile (top) and index (bottom) in the financial data. IGBC is in dashed line.

STAGE 1. Since there were missing data in these time series, we estimated them using the TSW package,[3] in order to work with complete time series. In Fig. 6 we plot the completed time series, jointly with the IGBC. We "standardized" the time series as described in the previous example.

STAGE 2. We detected 6 common factors in the transformed data and fitting model (1) with random-walk models for the common factors (because of the same reasons given in the economic application) and white-noise intrinsic processes, we found the estimated factors that are plotted in Fig. 7 and, as we can see there, the first factor resembles adequately well the IGBC.

STAGE 3. The above observation about the close relation between the first factor and IGBC is confirmed with the coincident profile that is shown in Fig. 8 (top), which has the highest p-value at lag zero when it is compared with the other factors.[4] Thus, this common factor can be seen as a coincident index for the state of the Colombian stock exchange, in the considered sample period.

STAGE 4. In the same Fig. 8 (bottom), we plot the proposed index based on January 2, 2010, and the IGBC and we can observe that the proposed index reflects very well the stylized facts of the Colombian stock market, specifically it shows the world's financial crisis in September 2008.

5. Conclusions

We have developed a procedure for choosing a reasonable, possibly non-stationary, common factor of a multivariate observable stochastic process, as a coincident index. The main tool to do that is the coincident profile, which uses the fact

3 This statistical package uses Gómez and Maravall's (1994) procedure for estimating missing data in ARIMA processes, via the Kalman filter.

4 We omit them because of space restrictions.

that a preliminary estimate for the state of the system is available. The proposed methodology was illustrated with two Colombian real-data applications; one, of the economy and the other, of the stock exchange. The results were satisfactory. Some important problems for future research are the following: (i) the selection of the common factor without using a preliminary estimate of the underlying system, (ii) study of deeper properties of the proposed statistical test, and (iii) the feasibility of choosing a linear combination of the common factors.

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