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Monitoring the Economy of the Euro Area: A Comparison of Composite Coincident Indexes*

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Abstract

Monitoring the current status of the economy is quite relevant for policy making but also for the decisions of private agents, consumers and firms. Since it is difficult to identify a single variable that provides a good measure of current economic conditions, it can be preferable to consider a combination of several coincident indicators, i.e., a composite coincident index (CCI). In this paper, we review the main statistical techniques for the construction of CCIs, propose a new pooling-based method, and apply the alternative techniques for constructing CCIs for the largest European countries in the euro area and for the euro area as a whole. We find that different statistical techniques yield comparable CCIs, so that it is possible to reach a consensus on the status of the economy.

Keywords: Business Cycles, Leading Indicators, Coincident Indicators, Turning Points, Forecasting

J.E.L. Classification: E32, E37, C53

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1 Introduction

Monitoring the current status of the economy is quite relevant for policy making but also for the decisions of private agents, consumers and firms. Unfortunately, there is no consensus in the literature on the selection of a measure of the current status of the economy, i.e., of a coincident indicator.

Paralleling the work by Moore and Shiskin (1967) for leading indicators, it is possible to list a set of properties that coincident indicators should exhibit. They include: (i) consistent timing as a coincident indicator (i.e., to systematically coincide with peaks and troughs in economic activity); (ii) economic significance (i.e., being supported by economic theory as good measures of economic activity); (iii) statistical reliability of data collection (i.e., provide an accurate measure of the quantity of interest); (iv) prompt availability without major later revisions (i.e., being timely and regularly available, without requiring subsequent modifications of the initial statements); (v) smooth month to month changes (i.e., being free of major high frequency movements).

Given these requirements, a natural choice for a coincident indicator is gross domestic product (GDP) or its growth rate, since it is typically considered as a reliable summary of the current economic conditions. Unfortunately, GDP is not available on a monthly basis and, although both in the US and in Europe there is a growing interest in increasing its sampling frequency from quarterly to monthly, the current results are still too preliminary to rely on them. Moreover, there are typically long delays in the release of GDP data and the preliminary values can be subject to subsequent large revisions. Both these features of the GDP data production process make it hardly usable as a timely coincident indicator.

In the past, industrial production (IP) provided a good proxy for the fluctuations of GDP, and it is still currently monitored for example by the NBER business cycle dating committee and by the Conference Board in the US (CB), in conjunction with other indicators, and by the OECD for several other countries. Yet, the ever rising share of services compared with the manufacturing, mining and gas and electric utility industries casts more and more doubts on the usefulness of IP as a single coincident indicator.

Another common indicator is the volume of sales of the manufacturing, wholesale and retail sectors, adjusted for price changes so as to proxy real total spending. Its main drawback, as in the case of IP, is its partial coverage of the economy.

A variable with a close to global coverage is real personal income less transfers, that underlies consumption decisions and aggregate spending. Yet, it is seldom available for European countries. Moreover, unusual productivity growth and favorable terms of trade can make income behave differently from payroll employment, the other most common indicator with economy wide coverage. Some authors focused on unemployment rather than employment, e.g. Boldin (1994) or Chin, Geweke and Miller (2000), on the grounds that the series is timely available and subject to minor revisions. Yet, typically unemployment is lagging and persistent rather than coincident, in particular in Europe.

Overall, it is difficult to identify a single variable that provides a good measure of current economic conditions, is available on a monthly basis, and satisfies all the requirements listed above. Therefore, it can be preferable to consider a combination of several coincident indicators, i.e., a composite coincident index (CCI).

In this paper we focus on the methodological aspects of constructing CCIs for the four largest countries in the euro area, and for the euro area as a whole, complementing the results in Marcellino (2005) for the US and in Carriero and Marcellino (2007a) for the UK. A composite coincident index (CCI) can be constructed in a non model based or in a model based framework. In the former, CCIs are simple weighted averages of selected single indicators. Examples are provided by the Conference Board and ECRI CCIs.

Within the model based approach, two main methodologies have emerged: dynamic factor models and Markov switching models. In both cases there is a single unobservable force underlying the current status of the economy, but in the former approach this is a continuous variable, while in the latter it is a discrete variable that evolves according to a Markov chain. Factor models provide a formalization of Burns and Mitchell's (1946) notion of business cycles as comovements in several variables. Leading references in the context of CCIs are Stock and Watson (1989, 1991, 1992), Forni, Lippi, Hallin, Reichlin (2001), Altissimo et al. (2001, 2006). Markov switching (MS) models formalize Burns and Mitchell's (1946) notion that expansions and recessions are different. After the pioneering article by Hamilton (1989), a vast literature followed, extending the basic model into several dimensions, e.g. Krolzig, Marcellino and Mizon (2002) consider multivariate MS error correction models, Diebold, Lee and Weinbach (1994) and Filardo (1994) allow the transition probabilities to depend on exogenous variables, while Diebold and Rudebusch (1996), Kim and Nelson (1998), Filardo and Gordon (1999) combine the characteristics of factor models and MS models by allowing MS features in the evolution of the factors.

In Section 2 we briefly review the econometrics of these alternative methods for the construction of a CCI. We also suggest a new pooling based approach. Since constructing a CCI can be considered as a problem of estimation of missing observations (about the status of the economy), the good performance of pooling emerging from the forecasting literature suggests that combining a set of competing CCIs can improve upon the quality of each of the single CCIs. The analysis is complicated by the fact that the forecasts can be compared with realized values after some time, while the status of the economy remains unobservable. This limits somewhat the range of feasible pooling techniques, as in the case of backdating or interpolation, see Marcellino (2007). Yet, simple combination methods such as averaging, possibly after trimming extreme values, work quite well in practice when compared with more sophisticated techniques, see e.g. Stock and Watson (1999) and Marcellino (2004).

In Section 3 we apply the alternative techniques for constructing CCIs for France, Germany, Italy and Spain. Since it is difficult to select a methodology from a theoretical point of view, we wish to consider whether they lead to major differences in the evaluation of the status of the economy, or whether a consensus can be achieved, as in the case of the US and UK, see Marcellino (2005) and Carriero and Marcellino (2007a). For simplicity and for the sake of comparability, rather than discussing in details the selection of the components of the CCIs for each country, we rely whenever possible on the variables included into the Conference Board coincident indexes for these European countries. The specific components of the index for each country are also discussed Section 3.

Since the evolution of the euro area as a whole is becoming more and more relevant from an economic and political point of view, in Section 4 we construct and compare alternative CCIs for the euro area, based on variables for the largest countries. Besides selecting an econometric technique, in this context we also have to deal with the multinational context. There are two possible strategies: aggregate the national CCIs, using GDP weights, or extract a CCI from a multinational dataset. The evidence in Marcellino, Stock and Watson (2003) suggests that the former strategy could be preferable, due to persisting differences across the member states. On the other hand, the latter could be favoured by the increased interaction among European countries.

Finally, Section 5 concludes with a summary of the main results we have obtained.

2 Constructing a composite coincident index

In this section we briefly review the main methods for the construction of a composite coincident index (CCI). We start with the non model based procedures and then discuss, in turn, factor based CCIs, Markow switching based CCIs, and pooling based CCIs. Additional details and references can be found, e.g., in Marcellino (2005).

2.1 Non-model-based CCI

In the non model based framework, the single components of the CCI are first transformed to have similar ranges, and then aggregated using equal or different weights. A clear illustration is provided by (a slightly simplified version of) the step-wise procedure implemented by the Conference Board (CB), see www.globalindicators.com for details, which we will use as a benchmark for comparison with more sophisticated methods.

First, for each individual indicator, x_{it}, month-to-month symmetric percentage changes (spc) are computed as $x_{it\_spc} = 200 * (x_{it} - x_{it-1})/(x_{it} + x_{it+1})$. Second, for each x_{it_spc} a volatility measure, v_i, is computed as the inverse of its standard deviation. Third, each x_{it_spc} is adjusted to equalize the volatility of the components, the standardization factor being $s_i = v_i/\sum_i v_i$. Fourth, the standardized components, $m_{it} = s_i x_{it\_spc}$, are summed together with equal weights, yielding $m_t = \sum_i m_{it}$. Fifth, the index in levels is computed as

$$CCI_t = CCI_{t-1} * (200 + m_t)/(200 - m_t) \tag{1}$$

with the starting condition

$$CCI_1 = (200 + m_1)/(200 - m_1).$$

Finally, rebasing CCI to average 100 in 1996 yields the CCI_{CB}.

2.2 Factor-based CCI

A dynamic factor model was used to extract a coincident indicator by Stock and Watson's (1989, SW), with subsequent refinements of the methodology in Stock and Watson (1991, 1992). The rationale of the approach is that all the coincident indicators are driven by a common force, the CCI, and by idiosyncratic components that are either uncorrelated across the variables under analysis or in any case common to only a limited subset of them. Hence, this approach formalizes Burns and Mitchell's (1946) notion that business cycles represent comovements in a set of series.

The particular model that SW adopted is the following,

$$\Delta x_t = \beta + \gamma(L)\Delta C_t + u_t \tag{2}$$

$$D(L)u_t = e_t \tag{3}$$

$$\phi(L)\Delta C_t = \delta + v_t \tag{4}$$

where x_t includes the components of the CCI, C_t is the single factor driving all variables, while u_t is the idiosyncratic component; Δ indicates the first difference operator, L is the lag operator and $\gamma(L)$, $D(L)$, $\phi(L)$ are, respectively, vector, matrix and scalar lag polynomials. SW used first differenced variables since unit root tests indicated that the coincident indexes were integrated, but not cointegrated. The model is identified by assuming that $D(L)$ is diagonal and e_t and v_t are mutually and serially uncorrelated at all leads and lags, which ensures that the common and the idiosyncratic components are uncorrelated. Moreover, ΔC_t should affect contemporaneously at least one coincident variable. Notice that the hypothesis of one factor, ΔC_t, does not mean that there is a unique source of aggregate fluctuations, but rather that different shocks have proportional dynamic effects on the variables.

For estimation, the model in (2)-(4) is augmented by the identity

$$C_{t-1} = \Delta C_{t-1} + C_{t-2,} \tag{5}$$

and cast into state-space form. The Kalman filter can then be used to write down the likelihood function, which is in turn maximized to obtain parameter and factor estimates, all the details are presented in Stock and Watson (1991).

A few additional comments are in order. First, the composite coincident index, CCI_{SWt}, is obtained through the Kalman filter as the minimum mean squared error linear estimator of C_t using information on the coincident variables up to period t. Hence, the procedure can be implemented in real time, conditional on the availability of data on the coincident variables. By using the Kalman smoother rather than the filter, it is possible to obtain end of period estimates of the state of the economy, i.e., $C_{t|T}$. Second, it is possible to obtain a direct measure of the contribution of each coincident indicator in x_t to the index by computing the response of the latter to a unit impulse in the former. Third, since data on some coincident indicator are published with delay, they can be treated as missing observations and estimated within the state-space framework. Moreover, the possibility of measurement error in the first releases of the coincident indicators can be also taken into consideration by adding an error term to the measurement equation. This is an important feature since data revisions are frequent and can be substantial, as for example testified by the revised US GDP growth rate data for 2001. Fourth, a particular time varying pattern in the parameters of the lag polynomials $D(L)$ and $\phi(L)$ can be allowed by using a time-varying transition matrix. Fifth, standard errors around the coincident index can be computed, even though they were not reported by SW.

A possible drawback of SW's procedure is that it requires an ex-ante classification of variables into coincident and leading or lagging, even though this is common practice in this literature, and it cannot be directly extended to analyze large datasets because of computational problems. Forni, Hallin, Lippi and Reichlin (2000, 2001 FHLR henceforth) proposed an alternative factor based methodology that addresses both issues, and applied it to the derivation of a composite coincident indicator for the Euro area. They analyzed a large set of macroeconomic time series for each country of the Euro area using a dynamic factor model, and decomposed each time series into a common and an idiosyncratic component, where the former is the part of the variable explained by common Euro area shocks, the latter by variable specific shocks. The CCI_{FHLR} is obtained as a weighted average of the common components of the interpolated monthly GDP series for each country, where the weights are proportional to GDP, and takes into account both within and across-countries cross correlations.

More specifically, the model FHLR adopted is

$$x_{it} = b_i^{'}(L)v_t + \xi_{it}, \quad i = 1, ..., N, \quad t = 1, ..., T, \tag{6}$$

where x_{it} is a stationary univariate random variable, v_t is a $q \times 1$ vector of common shocks, $\chi_{it} = x_{it} - \xi_{it}$ is the common component of x_{it}, and ξ_{it} is its idiosyncratic component. The shock v_t is an orthonormal white noise process, so that $var(v_{jt}) = 1$, $cov(v_t, v_{t-k}) = 0$, and $cov(v_{jt}, v_{st-k}) = 0$ for any $j \neq s$, t and k. $\xi_N = \{\xi_{1t}, ..., \xi_{Nt}\}^{'}$ is a wide sense stationary process, and $cov(\xi_{jt}, v_{st-k}) = 0$ for any j, s, t and k. $b_i(L)$ is a $q \times 1$ vector of square summable, bilateral filters, for any i. Notice that SW's factor model (2) is obtained as a particular case of (6) when there is one common shock ($q = 1$), $b_i(L) = \gamma_i(L)/\phi(L)$, and the idiosyncratic components are assumed to be orthogonal.

Grouping the variables into $x_{Nt} = \{x_{1t}, ..., x_{Nt}\}^{'}$, FHLR also required x_{Nt} (and χ_{Nt}, ξ_{Nt} that are similarly defined) to have rational spectral density matrices, Σ_N^x, Σ_N^χ, and Σ_N^ξ, respectively. To achieve identification, they assumed that the first (largest) idiosyncratic dynamic eigenvalue, λ_{N1}^ξ, is uniformly bounded, and that the first (largest) q common dynamic eigenvalues, $\lambda_{N1}^\chi, ..., \lambda_{Nq}^\chi$, diverge, where dynamic eigenvalues are the eigenvalues of the spectral density matrix, see e.g. Brillinger (1981, Chap. 9). In words, the former condition limits the effects of ξ_{it} on other cross-sectional units. The latter, instead, requires v_t to affect infinitely many units.

Let us assume for the moment that the number of common shocks is known. Then, FHLR suggested to estimate the common component of χ_{it} with the following step-wise procedure.

(i) Estimate the spectral density matrix of x_{Nt} as

$$\Sigma_N^T(\theta_h) = \sum_{k=-M}^{M} \Gamma_{Nk}^T \omega_k e^{-ik\theta_h}, \quad \theta_h = 2\pi h/(2M+1), \quad h = 0, ..., 2M, \tag{7}$$

where Γ_{Nk}^T is the sample covariance matrix of x_{Nt} and x_{Nt-k}, ω_k is the Bartlett lag window of size M ($\omega_k = 1 - k/(M+1)$), and M diverges but M/T tends to zero.

(ii) Calculate the first q eigenvectors of $\Sigma_N^T(\theta_h)$, $p_{Nj}^T(\theta_h)$, and the associated eigenvalues $\lambda_{j\theta}^x$, $j = 1, ..., q$, for $h = 0, ..., 2M$.

(iii) Define $p_{Nj}^T(L)$ as

$$p_{Nj}^T(L) = \sum_{k=-M}^{M} p_{Nj,k}^T L^k, \quad p_{Nj,k}^T = \frac{1}{2M+1}\sum_{h=0}^{2M} p_{Nj}^T(\theta_h)e^{ik\theta_h}, \quad k = -M, ..., M. \tag{8}$$

$p_{Nj}^T(L)x_{Nt}$, $j = 1, .., q$, are the first q estimated dynamic principal components of x_{Nt}.

(iv) The estimated common component of x_{it}, $\widehat{\chi}_{it}$, is the projection of x_{it} on present, past, and future dynamic principal components. FHLR proved that, under mild conditions, $\widehat{\chi}_{it}$ is a consistent estimator of χ_{it} when N and T diverge. Once the common component is estimated, the idiosyncratic one is obtained simply as a residual, namely, $\widehat{\xi}_{it} = x_{it} - \widehat{\chi}_{it}$. Therefore, each variable can be decomposed into

$$x_{it} = \widehat{\chi}_{it} + \widehat{\xi}_{it}. \tag{9}$$

In practice, M and the number of leads (s) and lags (g) of $p_{Nj}^T(L)x_{Nt}$ to be included in the projection can be either chosen a priori or determined by minimizing the information criterion

$$\frac{T}{N}\sum_{i=1}^{N} \log \widehat{\sigma}_i + 2q(g+s+1), \tag{10}$$

where $\widehat{\sigma}_i$ is the estimated variance of $\widehat{\xi}_{it}$. Finally, FHLR suggested to determine the number of factors, q, on the basis of two properties: (a) the average over frequencies of the first q dynamic eigenvalues diverges, while the average of the $q+1^{th}$ does not; (b) there should be a big gap between the variance of x_{Nt} explained by the first q dynamic principal components and that explained by the $q+1^{th}$ principal component. An information criterion could be also used. In particular, the criterion that FHLR suggested for selection of g and s, equation (10) above, could be minimized also with respect to q.

A competing procedure for the analysis of dynamic factor models with a large number of variables was developed by Stock and Watson (2002a, 2002b, SW2 henceforth). The model by SW2, in its time invariant formulation, can be written as

$$x_{nt} = \Lambda f_t + \xi_{nt}, \tag{11}$$

where f_t is an $r \times 1$ vector of common factors. Contrary to the specification by FHLR, the factors are not required to be uncorrelated in time, and they can be also correlated with the idiosyncratic component, only $var(f_t) = I$ is imposed for identification. Precise moment conditions on f_t and ξ_{nt}, and requirements on the loadings, are given in SW.

The specification in (11) is related to the one by FHLR in (6). When $b_i(L)$ is unilateral and of finite order b, say $b_i(L) = b_{0i} - b_{1i}L - b_{bi}L^b$, the model in (6) can be written as in

(11), where $f_t = (v_t, v_{t-1}, ..., v_{t-b})$ and the i^{th} row of Λ has elements b_{0i}, b_{1i}, b_{bi}. Hence, $r = q(b+1)$, and the factors f_t are dynamically singular, i.e., the spectral density matrix of f_t has rank q.

To estimate the factors, SW2 define the estimators $\widehat{f}_t$ as the minimizers of the objective function

$$V_{nT}(f, \Lambda) = \frac{1}{nT} \sum_{i=1}^{n} \sum_{t=1}^{T} (x_{it} - \Lambda_i f_t)^2. \tag{12}$$

Under the hypothesis of k common factors, it turns out that the optimal estimators of the factors are ($\sqrt{T}$ times) the k eigenvectors corresponding to the k largest eigenvalues of the $T \times T$ matrix $n^{-1} \sum_{i=1}^{n} \underline{x}_i \underline{x}_i^{'}$, where $\underline{x}_i = (x_{i1}, ..., x_{iT})$. These coincide with the principal components of the variables. Moreover, the optimal estimators of the loadings Λ are the OLS estimators of the coefficients in a regression of x_{it} on the k estimated factors $\widehat{f}_t$, $i = 1, ..., n$. Hence, a consistent estimator of the i^{th} common component can be obtained as $\widehat{\chi}_{it} = \widehat{\Lambda}_i \widehat{f}_t$, and a natural choice for the estimator of the idiosyncratic component is $\widehat{\xi}_{it} = x_{it} - \widehat{\chi}_{it}$.

A convenient feature of the SW2 approach is that no future information is used for factor estimation, contrary to FHLR, and therefore the method can be applied in real time. The CCI_{SW} can be defined either as the single factor extracted from a set of coincident indicators or as an average of the common components of each single indicator. We will report results for the former, since it provides a direct generalization of the procedure in Stock and Watson (1989).

The methodology by FHLR was further refined by Altissimo et al. (2001, 2006) for real time implementation, and it is currently adopted to produce the CEPR's composite coincident indicator for the euro area, Eurocoin (see www.cepr.org). In particular, they exploited the large cross-sectional dimension for forecasting indicators available with delay and for filtering out high frequency dynamics. However, the main innovation is the use of an alternative estimator for the common components of the variables which does not require future information. The theory for the latter is presented in Forni, Lippi, Hallin, Reichlin (2005, FHLR2 henceforth).

While the analytical derivation of the method in FHLR2 is fairly complicated, its practical implementation is relatively easy. Let us reconsider the decomposition in (9), namely,

$$x_{it} = \widehat{\chi}_{it} + \widehat{\xi}_{it}, \tag{13}$$

and indicate the variance covariance matrix of $\widehat{\xi}_t$ by V_ζ.

Using, for example, the standard Choleski decomposition, it is possible to find a matrix

P_ζ such that $P_\zeta V_\zeta P_\zeta' = I$. Multiplying both sides of (9) by P_ζ yields

$$P_\zeta x_{it} = P_\zeta \widehat{\chi}_{it} + P_\zeta \widehat{\xi}_{it} = \widehat{\alpha}_{it} + \widehat{\beta}_{it}, \tag{14}$$

where now the variance covariance of $\widehat{\beta}_t$ coincides with the identity matrix.

The principal components of $P_\zeta x_t$ are called generalized principal components of x_t by FHLR2, and the one-sided estimator of the common component is obtained by projecting the variables on the generalized principal components. Altissimo et al. (2001, 2006) construct Eurocoin as the weighted average of common components of interpolated monthly GDP of euro area countries. For comparability with the other CCIs we have constructed, we will instead focus on the first generalized principal component of x_t, CCI_{FHLR2}.

2.3 Markov-switching-based CCI

The main criticism Sims (1989) raised in his comment to Stock and Watson (1989) is the use of a constant parameter model (even though, as remarked above, their framework is flexible enough to allow for parameter variation), and a similar critique can be addressed to the FHLR's method. Hamilton's (1989) Markov switching model is a powerful response to this criticism, since it allows the growth rate of the variables (and possibly their dynamics) to depend on the status of the business cycle. A basic version of the model can be written as

$$\Delta x_t = c_{s_t} + A_{s_t} \Delta x_{t-1} + u_t, \tag{15}$$

$$u_t \sim i.i.d.N(0, \Sigma) \tag{16}$$

where, as in (2), x_t includes the coincident variables under analysis (or a single composite index), while s_t measures the status of the business cycle, with $s_t = 1$ in recessions and $s_t = 0$ in expansions, and both the deterministic component and the dynamics can change over different business cycle phases. The binary state variable s_t is not observable, but the values of the coincident indicators provide information on it.

With respect to the factor model based analysis, there is again a single unobservable force underlying the evolution of the indicators but, first, it is discrete rather than continuous and, second, it does not directly affect or summarize the variables but rather indirectly determines their behaviour that can change substantially over different phases of the cycle.

To close the model and estimate its parameters, an equation describing the behaviour of s_t is required, and it cannot be of autoregressive form as (4) since s_t is a binary variable.

Hamilton (1989) proposed to adopt the Markov switching (MS) model, where

$$\Pr(s_t = j | s_{t-1} = i) = p_{ij}, \tag{17}$$

as previously considered by Lindgren (1978) and Neftci (1982) in simpler contexts. For expositional purposes we stick to the two states hypothesis, though there is some empirical evidence that three states can further improve the specification, representing recession, high growth and normal growth, see e.g. Kim and Murray (2002) for the US and Artis, Krolzig and Toro (2003) for the Euro area.

In our business cycle context, the quantity of special interest is an estimate of the unobservable current status of the economy and, assuming a mean square error loss function, the best estimator coincides with the conditional expectation of s_t given current and past information on x_t, which in turn is equivalent to the conditional probability

$$\zeta_{t|t} = \begin{pmatrix} \Pr(s_t = 0 | x_t, x_{t-1}, ..., x_1) \\ \Pr(s_t = 1 | x_t, x_{t-1}, ..., x_1) \end{pmatrix}. \tag{18}$$

Using simple probability rules, it follows that

$$\zeta_{t|t} = \begin{pmatrix} \frac{f(x_t | s_t = 0, x_{t-1}, ..., x_1) \Pr(s_t = 0 | x_{t-1}, ..., x_1)}{f(x_t | x_{t-1}, ..., x_1)} \\ \frac{f(x_t | s_t = 1, x_{t-1}, ..., x_1) \Pr(s_t = 1 | x_{t-1}, ..., x_1)}{f(x_t | x_{t-1}, ..., x_1)} \end{pmatrix}, \tag{19}$$

where

$$\Pr(s_t = i | x_{t-1}, ..., x_1) = \sum_{j=0}^{1} p_{ji} \Pr(s_{t-1} = j | x_{t-1}, ..., x_1), \tag{20}$$

$$f(x_t | s_t = i, x_{t-1}, ..., x_1) = \frac{|\Sigma|^{-1/2}}{(2\pi)^{T/2}} \exp[-(\Delta x_t - c_i - A_i \Delta x_{t-1})' \Sigma^{-1} (\Delta x_t - c_i - A_i \Delta x_{t-1})/2], \tag{21}$$

$$f(x_t, s_t = i | x_{t-1}, ..., x_1) = f(x_t | s_t = i, x_{t-1}, ..., x_1) \Pr(s_t = i | x_{t-1}, ..., x_1),$$

$$f(x_t | x_{t-1}, ..., x_1) = \sum_{j=0}^{1} f(x_t, s_t = j | x_{t-1}, ..., x_1), \quad i = 0, 1.$$

Hamilton (1994) or Krolzig (1997) provide additional details on these computations, and formulae to calculate $\zeta_{t|T}$, i.e., the smoothed estimator of the probability of being in a given status in period t. Notice also that the first and last rows of (20) provide, respectively, the probability of the state and the density of the variables conditional on past information only.

The model in (15)-(17) can be extended in several dimensions, for example to allow for more states and cointegration among the variables, see e.g. Krolzig, Marcellino and Mizon (2002), or time-varying probabilities, as e.g. in Diebold, Lee and Weinbach (1994) or Filardo (1994).

Factor models and Markov switching specifications capture two complementary and fundamental features of business cycles, namely, the diffusion of slow-down and recovery across many series and the different behavior of several indicators in expansions and recessions. They are not only flexible and powerful statistical tools but can be also given sound justifications from an economic theory point of view, see e.g. the overview in Diebold and Rudebusch (1996). The latter article represents also one of the earliest attempts to combine the two approaches, by allowing the factor underlying SW's model to evolve according to a Markov switching model. Yet, Diebold and Rudebusch (1996) did not jointly estimate the factor MS model. Such a task was tackled by Chauvet (1998) and Kim and Yoo (1995), using an approximated maximum likelihood procedure developed by Kim (1994), and by Kim and Nelson (1998) and Filardo and Gordon (1999) using Gibbs sampler techniques introduced by Albert and Chib (1993), Carter and Kohn (1994), and Shepard (1994).

2.4 Pooling-based CCI

Since the pioneering work of Bates and Granger (1969), it is well known that pooling can improve forecasting, i.e. estimating missing observations at the end of the sample, and there now exists a vast amount of empirical evidence to support their claim, see e.g. Timmermann (2005) for a recent overview. As discussed by Hendry and Clements (2004), possible reasons for the good performance of forecast pooling may be model misspecification and parameter non-constancy that are attenuated by weighting. Marcellino (2007) shows that pooling is also quite effective for backdating and data interpolation, i.e. for estimating missing observations at the beginning or elsewhere in the sample.

Since constructing a CCI can be considered as a problem of estimation of missing observations (about the status of the economy), the cited evidence on the good performance of pooling suggests that combining a set of competing CCIs can improve upon the quality of each of the single CCIs.

The analysis is complicated by the fact that the forecasts can be compared with realized values after some time, while the status of the economy remains unobservable. This limits somewhat the range of feasible pooling techniques, as in the case of backdating or interpolation. Yet, simple combination methods such as averaging, possibly after trimming extreme values, work quite well in practice when compared with more sophisticated techniques, see e.g. Stock and Watson (1999) and Marcellino (2007).

Therefore, we will also experiment with averages of the single CCIs we described in the previous subsections, and we think that this is the first time that pooling is applied in the context of the construction of a composite coincident index, even though the construction of the non-model based indexes closely mimics pooling.

We will now apply the techniques reviewed so far for the construction of CCIs for the four largest countries in the euro area.

3 CCIs for European countries

We focus on the variables included into the CB coincident indexes for the European countries under analysis, in order to have a benchmark for the alternative CCI construction methods and avoid issues related with variable selection and transformation, even though the latter are very important, see e.g. Marcellino (2005) for details.

The variables and the sample period can differ across countries due to data availability. In particular, we have the following list.

- France: Retail sales, Industrial Production, Real Imports, Paid Employment, Sample 1970:3-2005:3.
- Germany: Manufacturing Sales, Industrial Production, Retail sales, Employment (Persons Employed). Sample 1994:3-2005:3.
- Spain: Final Household Consumption, Industrial Production (Excluding Construction), Real Imports, Retail Sales Survey. Sample 1985:1-2005:3.

We have also collected data for Italy, since it is not considered by the CB. In particular,

- Italy: Industrial Production, Unemployment rate, Compensations of Employees, Real Household Disposable Income. Sample 1980:1-2004:11.

The (logs of the) variables for each country are graphed in Figure 1, after normalization. Overall, the indicators for each country follow the same trend and their peaks and troughs structure at the quarterly level mimics that of GDP growth, as we will see later on. However, there are also evident differences in the behaviour of the single indicators for each country, which provides support for their combination into a CCI rather than for the selection of a single indicator.

In Figures 2 and 3 we graph the original CB CCIs and our replications using the slightly simplified methodology described in the previous Section. The two indexes are basically the same both in levels and in growth rates, the structure of peaks and troughs is unaltered and the correlations between the levels or the 6-month growth rates of the original index and our replication are higher than 0.95. Therefore, in the following analysis, we will use our non-model based index as a benchmark for each country, referring to it as NMB.

3.1 Factor-based CCIs

The factor-based methods for the construction of a CCI described in the previous Section require the input variables to be stationary. From the graphs in Figure 1 the single coincident indicators present either a trending behaviour or at least persistent deviations from the mean. These features are confirmed by unit root tests, which do not reject the null hypothesis of a unit root for any of the indicators. Therefore, as SW and FHLR, we will work with the (month on month) growth rates of the single indicators.

All the factor based methods we have described do not take cointegration across the single indicators into account. The omission of an error correction term can be a serious issue, see e.g. Emerson and Hendry (1996) in a related context. SW mention that they tested for the presence of cointegration but none was found. In our case, from the list of the indicators described above, there are no strong economic reasons for the presence of cointegration. However, for each country, we have tested for cointegration within a VAR model. The results, available upon request, vary substantially depending on the lag length, the deterministic component included into the VAR, and the type of cointegration test applied (Johansen's (1988) trace or eigenvalue statistic). When BIC is used to select the lag length of the VAR and the deterministic component, it then also selects models without cointegration for France, Germany, and Italy, while it indicates the presence of one cointegration relationship for Spain. On the basis of this outcome and for the sake of comparability across countries, we will continue our analysis under the assumption of no cointegration.

To start with, we adopt a parametric factor model as in SW and we construct the CCI_{SW} as the (cumulated) estimated factor C_{ct}, $c =$ France, Germany, Italy, Spain. For each country, we consider the following specification, where the variables are the demeaned log differences of the levels:

$$\begin{cases} y_{1ct} = \gamma_{1c}\Delta C_{ct} + u_{1ct} \\ y_{2ct} = \gamma_{2c}\Delta C_{ct} + u_{2ct} \\ y_{3ct} = \gamma_{3c}\Delta C_{ct} + u_{3ct} \\ y_{4ct} = \gamma_{4c}\Delta C_{ct} + u_{4ct} \\ u_{ict} = \psi_{1ic}u_{ict-1} + \psi_{2ic}u_{ict-2} + \varepsilon_{ict}; \quad \varepsilon_{ict} \sim iidN(0, \sigma^2_{ic}); \quad i = 1,2,3,4; \\ \Delta C_{ct} = \varphi_1 \Delta C_{ct-1} + \varphi_2 \Delta C_{ct-2} + v_{ct}; \quad v_{ct} \sim iidN(0,1) \\ COV(\varepsilon_{ict}, v_{cs}) = 0 \ \forall c, \ \forall i, \ \forall s, \ \forall t \end{cases} \tag{22}$$

Table 1 reports the p-values of some standard tests for homoskedasticity, normality and lack of correlation of the disturbances ε_{ict}. The major problems are detected for Italy, but normality is also often rejected for the other countries. The latter problem is caused by a few outlying observations, but it can be hardly eliminated by inserting dummy variables into the models. A more detailed specification search has shown that increasing the number of lags or tailoring the specification for each variable and country does not improve substantially the outcome of the diagnostic tests, but it also does not alter significantly the estimated factor, suggesting that the resulting indicator is rather robust to model specification. Therefore, we will stick to the specification in (22).

A possible solution to address the partial misspecification of the parametric factor model in (22) is to resort to nonparametric techniques to estimate the common factor and obtain alternative factor-based CCIs. Though the methods by FHLR2 and SW2 are particularly suited when the number of variables under analysis is large, it is interesting to evaluate their performance in our context.

With reference to the models in the previous Section, for SW2 we use one factor and for FHLR2 we set the bandwidth parameter at M=12 and use one factor both in the first step (i.e. to compute the variance covariance matrix of the common components obtained using FHLR) and in the second step.

In Figure 4 we graph the (standardized) NMB CCI, the three versions of the factor based CCIs, namely, SW, SW2 and FHLR2, and the CCI obtained by pooling all these CCIs. All indexes tend to move closely together. The visual impression is confirmed by the correlations reported in the panel A of Tables 2-5.

A similar finding emerges from the 6-month growth rates of the CCIs, Figure 5, and from the bandpass filtered CCIs where we apply the bandpass HP filter proposed in Artis, Marcellino, Proietti (2004) to emphasize the business cycle frequencies (between 1.5 and 8 years), Figure 6. The related correlations are reported in the panels B and C of Tables 2-5. They remain quite high, with the lowest values typically achieved either by SW with either NMB or FHLR2 (still these values are larger than 0.75), and figures typically higher than 0.90 for SW2 and FHLR2. The use of growth rates or filtered data also emphasizes the close similarity of the indexes at turning points.

We then aggregate the monthly values to quarterly, and compare the indexes across themselves and with real GDP growth. The results for levels and two quarter growth rates are reported for each country in panels D and E of Tables 2-5. The similarity across the indexes is confirmed at the quarterly frequency. In terms of correlation with GDP growth, the highest values are in the range 0.70-0.81 and are achieved by SW2 for France and Italy, by FHLR2 for Spain, and by NMB for Germany, with overall minor differences across the alternative CCIs, except for Italy where NMB and SW yield sensibly lower values.

The pooled CCI obtained by averaging the CCI_{NMB} and the three factor based CCIs is, obviously, very similar to each of its components but does not yield any substantial gains in terms of correlation with GDP, even though it is the second best for Italy and for France when comparing the 6 month growth rates. From the forecasting literature, the absence of major gains from pooling is likely due to the high correlation of the combined CCIs, which decreases the usefulness of pooling them.

Finally, we would like to mention that the comparison with GDP growth should be interpreted with care. Even though such a comparison is standard in the literature, it is not clear that GDP is a good overall measure of the status of the economy, for the reasons discussed before. Moreover, GDP growth can be uncorrelated with higher employment or disposable income, as the recent prolonged jobless recovery in the US or the persistently high unemployment rates in Europe testify.

3.2 Markov-switching-based CCIs

To evaluate the usefulness of the Markov-switching approach for the construction of CCIs for European countries, we have estimated for each country the MS-VAR(1) model

$$\Delta x_t = c_{s_t} + A\Delta x_{t-1} + u_t, \quad u_t \sim i.i.d.N(0, \Sigma), \tag{23}$$

where s_t is the binary expansion / recession indicator. More complicated specifications, with additional lags or switching in the other parameters, are typically hardly estimable in our context, due to the rather short sample available and the limited number of cycles.

In Figure 7 we compare the smoothed probability of recession resulting from the MS-VAR with the 6 month growth rate in the CCI_{NMB}. We would expect higher probability of recessions associated with marked slowdowns in the growth of the CCI_{NMB}. This appears to be the case for Italy, where the major recessions, as dated by Artis et al. (2004), are associated with increases in the probability of recession. However, the picture is different for Spain, where in a few cases the estimated probability of recession is high even when the CCI_{NMB} does not signal major problems, and for France and Germany, where the probability of recession is close to one too frequently. Similar results are obtained with the filtered probabilities, which are recursively evaluated rather than based on the full sample, see Figure 8.

Overall, at least for the sample period and time series we consider, there seem to be minor or no gains from the construction of MS based CCIs with respect to the factor based ones.

4 CCIs for the European Union and the euro area

The evolution of the euro area as a whole is becoming more and more relevant from an economic and political point of view. It is therefore important to construct CCIs also for the euro area.

There are two possible strategies: aggregate the national CCIs, using GDP weights, or extract a CCI from a multinational dataset. The former approach is better suited in the presence of remaining heterogeneity across the countries. The latter, on the other hand, allows for interaction across the countries, which can be important in a context of increasing linkages. When using the multinational dataset, the parametric SW method is no longer feasible due to the increased size of the dataset, while FHLR2 and SW2 should perform even better for the same reason.

Table 6 reports the correlation at a monthly and quarterly frequency for the indexes for the euro area obtained by aggregating the national CCIs, over the common sample 1994:3-2004:11. Table 7 presents similar figures for the indexes extracted from a pooled dataset for France, Germany, Italy, and Spain. We refer to the resulting indexes as "aggregate" and "euro", respectively, and graph them in Figure 9. The tables suggest that also in this context the factor-based methods produce very similar indexes, which in turn are basically equivalent to the CCI_{NMB}. Moreover, from the figure, the peak and trough structure of the aggregate and euro indexes is highly comparable, in particular for the factor-based ones. Focusing on the correlations with the 2-quarters real EA GDP growth, all figures are above 0.80, with the highest value for the NMB pooled dataset index, 0.87.

Next, we compare our coincident indexes (both obtained by simple aggregation of national CCIs and obtained with the pooled dataset) to the (New-)Eurocoin indicator of Altissimo et al. (2006), which is the coincident indicator of the euro area business cycle produced by the CEPR, and to the Economic Sentiment Indicator, which is produced by DG-ECFIN on the basis of the answers to regular surveys for different sectors of the economies in the European Union.

Panel A of Table 8 displays the correlations of our alternative CCIs with the Eurocoin indicator. The highest correlation is with the aggregate CCI_{FHLR2}, 0.82, the lowest with the euro CCI_{NMB}, 0.76. The CCI_{FHLR2}, constructed with a similar methodology as Eurocoin but using a much smaller information set, has correlations 0.82 and 0.77 for, respectively, the euro and aggregate versions. Notice that in this case we compare 3 month percentage changes, since this is the unit of measurement of Eurocoin.

In panel B of Table 8 we then compare the one quarter percentage changes in our CCIs and Eurocoin with that of Euro area real GDP. The highest correlation is achieved by aggregated CCI_{NMB}, 0.78, the lowest by euro CCI_{FHLR2}, 0.65. Interestingly, all the indexes obtained by simple aggregation of national CCIs outperform both the indexes obtained with the pooled dataset and the Eurocoin. This is an interesting finding since Eurocoin is constructed as an average of the permanent components of interpolated monthly GDP and could therefore be expected to be more correlated with quarterly GDP than our indexes. Figure 10 indicates that all CCIs closely track the ups and downs of euro area GDP growth, perhaps Eurocoin only missed the recent slowdown in 2003.

Finally, we contrast our CCIs with the Economic Sentiment Indicator (ESI) constructed by the European Commission using simple averaging methods.[1]

Table 9 reports results for the euro area while Table 10 reports results for the single member states. Panel A of Table 9 displays the correlations of our alternative CCIs with the ESI for the euro area. Correlations of our indexes with the ESI are slightly lower than with Eurocoin, ranging from 0.549 of euro CCI_{SW2} to 0.702 of aggregated CCI_{NMB}.

Panel B of Table 10 reports the correlations between the indexes and the annual GDP growth rate, the chosen benchmark by the Commission.[2]. The euro CCI_{NMB} provides the highest correlation with GDP growth, 0.95, but also all the indexes obtained by simple aggregation of national CCIs have a correlation above 0.90, outperforming the ESI indicator. These values are remarkably high, and also indicate that the behaviour of the alternative CCIs are very similar, see Figure 11.

Results for the single European countries are displayed in Table 10. The highest correlation with GDP growth are achieved either by CCI_{NMB} (France, Germany and Spain) or by CCI_{FHLR2} (Italy).

In summary, there is no clear cut ranking of the aggregation versus pooling approaches to construct European or euro area CCIs, but the results are highly comparable. Competing indicators such as Eurocoin, which relies on the same methodology as CCI_{FHLR2} but a much larger macroeconomic information set, and the ESI, which is based on the answers to a very large business and consumer survey, do not seem to yield any major gains with respect to our simpler alternatives. However, an interesting additional feature of the ESI is the very timely availability and lack of revision of its survey-based components. The combination of these components using factor based methods rather than simple averaging is considered in Carriero and Marcellino (2007b).

[1]Details on the ESI are available at http://europa.eu.int/comm/economy_finance/indicators/business_consumer_surveys/userguide_en.pdf

[2]See, e.g.http://europa.eu.int/comm/economy_finance/indicators/business_consumer_surveys/methodological_esi_note_052004_en.pdf

5 Conclusions

In this paper we have compared a variety of statistical methods for the construction of composite coincident indexes to monitor economic conditions in the euro area, and proposed and evaluated a novel pooling-based procedure.

Simple non model based CCIs for the European countries, which are averages of standardized selected single coincident indicators, yield in general similar results as more complicated methods. However, the more sophisticated model based methods can provide a statistical framework for the computation of standard errors around the CCI, the unified treatment of data revisions and missing observations, and the development of composite leading indexes (see e.g. Marcellino (2005a)).

Among the model based approaches to CCIs construction, factor based methods provide good results, with limited estimation problems even with short time series. Markov switching methods are interesting but, with the short and noisy time series typically available for Europe, estimation can be a serious issue.

Pooling is not particularly helpful in this context, likely due to the high correlation across the combined CCIs. It can improve the correlation with GDP growth for a few countries, but in general the gains are minor.

On the other hand, the good performance of the CCIs_{NMB} can be related to pooling, where single rather than composite indicators are combined, which increases their variability. This is particularly evident at the euro area level, where the CCI_{NMB} often yields the highest correlation with GDP growth. However, the differences with respect to the aggregate or euro versions of the other CCIs are minor.

Finally, our rather simple CCIs are also comparable with Eurocoin, produced by the CEPR relying on the methodology developed by Altissimo et al. (2001, 2006) and a very large set of hundreds of macroeconomic variables, and with the Economic Sentiment Indicator, which is produced by the European Commission using the responses from a large survey.

Overall, the results in this paper indicate that it is possible to achieve a substantial consensus on the current status of the economy, which is an important finding for economic policy and, more generally, for decision making.

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TABLE 1: P-values of diagnostic tests on the residuals of the parametric factor model

	$i=1$	$i=2$	$i=3$	$i=4$
France				
Homoskedasticity (White)	0.000	0.182	0.639	0.000
No autocorrelation (Breush Godfrey)	0.355	0.008	0.999	0.571
Normality (Jarque Bera)	0.073	0.000	0.000	0.357
Germany				
Homoskedasticity (White)	0.020	0.036	0.346	0.828
No autocorrelation (Breush Godfrey)	0.016	0.000	0.418	0.211
Normality (Jarque Bera)	0.000	0.000	0.398	0.000
Italy				
Homosckedasticity (White)	0.000	0.045	0.019	0.023
No autocorrelation (Breush Godfrey)	0.001	0.999	0.000	0.000
Normality (Jarque Bera)	0.000	0.000	0.000	0.000
Spain				
Homoskedasticity (White)	0.137	0.002	0.611	0.681
No autocorrelation (Breush Godfrey)	0.000	0.025	0.999	0.999
Normality (Jarque Bera)	0.000	0.010	0.000	0.000

The Table reports the p-values of standard tests for homoskedasticity, normality and lack of correlation of the disturbance term ε_{ict} in the model in (22). The letter c denotes the country: $c =$ France, Germany, Italy, Spain. For each country, $i = 1, 2, 3, 4$ denotes the equation associated to each variable. For France $i =$ Retail sales, Industrial Production, Real Imports, Paid Employment. For Germany $i =$ Manufacturing Sales, Industrial Production, Retail sales, Employment (Persons Employed). For Spain $i =$ Final Household Consumption, Industrial Production (Excluding Construction), Real Imports, Retail Sales Survey. For Italy $i =$ Industrial Production, Unemployment rate, Compensations of Employees, Real Household Disposable Income. Samples are: France 1970:3-2005:3, Germany 1994:3-2005:3, Spain 1985:1-2005:3, Italy 1980:1-2004:11.

TABLE 2: France, Correlations of alternative CCIs

Monthly data

A. Levels	NMB	SW	FHLR2	SW2	POOL
NMB	1	0.990	0.998	0.999	0.998
SW		1	0.992	0.990	0.995
FHLR2			1	0.999	0.999
SW2				1	0.999
POOL					1

B. 6 months % change	NMB	SW	FHLR2	SW2	POOL
NMB	1	0.812	0.891	0.949	0.948
SW		1	0.775	0.788	0.891
FHLR2			1	0.973	0.962
SW2				1	0.981
POOL					1

C. Filtered data	NMB	SW	FHLR2	SW2	POOL
NMB	1	0.812	0.891	0.949	0.948
SW		1	0.775	0.788	0.891
FHLR2			1	0.973	0.962
SW2				1	0.981
POOL					1

Quarterly data

D. Levels	NMB	SW	FHLR2	SW2	POOL	RGDP
NMB	1	0.989	0.998	0.999	0.998	0.990
SW		1	0.992	0.990	0.995	0.996
FHLR2			1	0.999	0.999	0.991
SW2				1	0.999	0.989
POOL					1	0.993
RGDP						1

E. 2 quarters % change	NMB	SW	FHLR2	SW2	POOL	RGDP
NMB	1	0.827	0.912	0.961	0.955	0.778
SW		1	0.815	0.821	0.909	0.682
FHLR2			1	0.979	0.970	0.775
SW2				1	0.984	0.811
POOL					1	0.801
RGDP						1

The table displays the correlations of alternative CCIs. CCIs are: NMB: Non -model-based, SW: Stock and Watson's (1989), FHLR2: Forni, Hallin, Lippi, and Reichlin (2005), SW2: Stock and Watson (2002a,b), POOL: pooling of all CCIs. RGDP is real GDP. Panels A, B, C are based on monthly data and contain respectively results for the level of CCIs, the 6 month %change in CCIs, and for the CCIs filtered as in Artis, Marcellino, Proietti (2004). Panels D and E are based on quarterly data and contain respectively results for the level of CCIs and the 2 quarters %change in CCIs. Sample is 1970:3 2005:3

TABLE 3: Germany, Correlations of alternative CCIs

Monthly data

A. Levels	NMB	SW	FHLR2	SW2	POOL
NMB	1	0.983	0.996	0.992	0.991
SW		1	0.994	0.996	0.997
FHLR2			1	0.999	0.999
SW2				1	0.999
POOL					1

B. 6 months % change	NMB	SW	FHLR2	SW2	POOL
NMB	1	0.914	0.981	0.954	0959
SW		1	0.954	0.944	0968
FHLR2			1	0.990	0994
SW2				1	0996
POOL					1

C. Filtered data	NMB	SW	FHLR2	SW2	POOL
NMB	1	0.915	0.973	0.926	0.947
SW		1	0.951	0.927	0.964
FHLR2			1	0.983	0.990
SW2				1	0.990
POOL					1

Quarterly data

D. Levels	NMB	SW	FHLR2	SW2	POOL	RGDP
NMB	1	0.988	0.998	0.996	0.995	0.958
SW		1	0.994	0.995	0.997	0.978
FHLR2			1	0.999	0.999	0.968
SW2				1	0.999	0.971
POOL					1	0.973
RGDP						1

E. 2 quarters % change	NMB	SW	FHLR2	SW2	POOL	RGDP
NMB	1	0.926	0.987	0.970	0.972	0.720
SW		1	0.958	0.946	0.970	0.676
FHLR2			1	0.993	0.996	0.709
SW2				1	0.996	0.681
POOL					1	0.691
RGDP						1

The table displays the correlations of alternative CCIs. CCIs are: NMB: Non -model-based, SW: Stock and Watson (1989), FHLR2: Forni, Hallin, Lippi, and Reichlin (2005), SW2: Stock and Watson (2002a,b), POOL: pooling of all CCIs. RGDP is real GDP. Panels A, B, C are based on monthly data and contain respectively results for the level of CCIs, the 6 month %change in CCIs, and for the CCIs filtered as in Artis, Marcellino, Proietti (2004). Panels D and E are based on quarterly data and contain respectively results for the level of CCIs and the 2 quarters %change in CCIs. Sample is 1994:3-2005:3.

TABLE 4: Italy, Correlations of alternative CCIs

Monthly data

A. Levels	NMB	SW	FHLR2	SW2	POOL
NMB	1		0.992	0.994	0.997
SW		1	0.975	0.986	0.989
FHLR2			1	0.989	0.994
SW2				1	0.998
POOL					1

B. 6 months % change	NMB	SW	FHLR2	SW2	POOL
NMB	1	0.820	0.810	0.792	0.882
SW		1	0.459	0.649	0.702
FHLR2			1	0.861	0.911
SW2				1	0.981
POOL					1

C. Filtered data	NMB	SW	FHLR2	SW2	POOL
NMB	1	0.762	0.892	0.863	0.924
SW		1	0.575	0.735	0.749
FHLR2			1	0.905	0.943
SW2				1	0.985
POOL					1

Quarterly data

D. Levels	NMB	SW	FHLR2	SW2	POOL	RGDP
NMB	1	0.992	0.993	0.994	0.997	0.976
SW		1	0.977	0.986	0.989	0.968
FHLR2			1	0.991	0.995	0.967
SW2				1	0.998	0.988
POOL					1	0.981
RGDP						1

E. 2 quarters % change	NMB	SW	FHLR2	SW2	POOL	RGDP
NMB	1	0.836	0.813	0.800	0.886	0.452
SW		1	0.489	0.670	0.721	0.422
FHLR2			1	0.866	0.915	0.574
SW2				1	0.982	0.709
POOL					1	0.656
RGDP						1

The table displays the correlations of alternative CCIs. CCIs are: NMB: Non -model-based, SW: Stock and Watson (1989), FHLR2: Forni, Hallin, Lippi, and Reichlin (2005), SW2: Stock and Watson (2002a,b), POOL: pooling of all CCIs. RGDP is real GDP. Panels A, B, C are based on monthly data and contain respectively results for the level of CCIs, the 6 month %change in CCIs, and for the CCIs filtered as in Artis, Marcellino, Proietti (2004). Panels D and E are based on quarterly data and contain respectively results for the level of CCIs and the 2 quarters %change in CCIs. Sample is 1985:1-2005:3.

TABLE 5: Spain, Correlations of alternative CCIs

Monthly data

A. Levels	NMB	SW	FHLR2	SW2	POOL
NMB	1	0.986	0.995	0.999	0.998
SW		1	0.975	0.982	0.993
FHLR2			1	0.995	0.992
SW2				1	0.996
POOL					1

B. 6 months % change	NMB	SW	FHLR2	SW2	POOL
NMB	1	0.817	0.902	0.986	0.950
SW		1	0.724	0.753	0.951
FHLR2			1	0.909	0.873
SW2				1	0.918
POOL					1

C. Filtered data	NMB	SW	FHLR2	SW2	POOL
NMB	1	0.833	0.868	0.984	0.944
SW		1	0.790	0.794	0.962
FHLR2			1	0.876	0.886
SW2				1	0.926
POOL					1

Quarterly data

D. Levels	NMB	SW	FHLR2	SW2	POOL	RGDP
NMB	1	0.987	0.994	0.999	0.998	0.998
SW		1	0.979	0.984	0.994	0.982
FHLR2			1	0.995	0.992	0.991
SW2				1	0.997	0.998
POOL					1	0.995
RGDP						1

E. 2 quarters % change	NMB	SW	FHLR2	SW2	POOL	RGDP
NMB	1	0.839	0.942	0.990	0.954	0.664
SW		1	0.793	0.790	0.960	0.616
FHLR2			1	0.943	0.914	0.721
SW2				1	0.929	0.647
POOL					1	0.670
RGDP						1

The table displays the correlations of alternative CCIs. CCIs are: NMB: Non -model-based, SW: Stock and Watson (1989), FHLR2: Forni, Hallin, Lippi, and Reichlin (2005), SW2: Stock and Watson (2002a,b), POOL: pooling of all CCIs. RGDP is real GDP. Panels A, B, C are based on monthly data and contain respectively results for the level of CCIs, the 6 month %change in CCIs, and for the CCIs filtered as in Artis, Marcellino, Proietti (2004). Panels D and E are based on quarterly data and contain respectively results for the level of CCIs and the 2 quarters %change in CCIs. Sample is 1980:1-2004:11.

TABLE 6: EA, Correlations of alternative CCIs (aggregate of national CCIs)

A: Monthly data	Agg. NMB	Agg. FHLR2	Agg. SW2	
Levels				
Aggregate NMB	1	0.997	0.994	
Aggregate FHLR2		1	0.999	
Aggregate SW2			1	
6 months % change				
Aggregate NMB	1	0.949	0.960	
Aggregate FHLR2		1	0.991	
Aggregate SW2			1	
B: Quarterly data	Agg. NMB	Agg. FHLR2	Agg. SW2	EA GDP
Levels				
Aggregate NMB	1	0.997	0.994	0.991
Aggregate FHLR2		1	0.999	0.984
Aggregate SW2			1	0.977
EA GDP				1
2 quarters % change				
Aggregate NMB	1	0.953	0.962	0.850
Aggregate FHLR2		1	0.992	0.848
Aggregate SW2			1	0.852
EA GDP				1

The Table reports the correlation at a monthly and quarterly frequency for the indexes for the euro area obtained by aggregating the national CCIs, over the common sample 1994:3-2004:11. CCIs are: NMB: Non -model-based, FHLR2: Forni, Hallin, Lippi, and Reichlin (2005), SW2: Stock and Watson (2002a,b). EA GDP is Euro Area real GDP. Panel A is based on monthly data and contains results for the level and 6 month %change in CCIs. Panel B is based on quarterly data and contains results for the level and 2 quarters %change in CCIs

TABLE 7: EA, Correlations of alternative CCIs (pooled dataset)

A: Monthly data	Euro NMB	Euro FHLR2	Euro SW2
Levels			
Euro Area NMB	1	0.997	0.997
Euro Area FHLR2		1	0.999
Euro Area SW2			1
6 months % change			
Euro Area NMB	1	0.877	0.919
Euro Area FHLR2		1	0.941
Euro Area SW2			1

B: Quarterly data	Euro NMB	Euro FHLR2	Euro SW2	EA GDP
Levels				
Euro Area NMB	1	0.997	0.997	0.999
Euro Area FHLR2		1	0.999	0.997
Euro Area SW2			1	0.996
EU15. GDP				1
2 quarters % change				
Euro Area NMB	1	0.889	0.924	0.872
Euro Area FHLR2		1	0.949	0.803
Euro Area SW2			1	0.821
EA GDP				1

The Table reports the correlation at a monthly and quarterly frequency for the indexes for the euro area obtained by pooling the datasets. The common sample is 1994:3-2004:11. CCIs are: NMB: Non -model-based, FHLR2: Forni, Hallin, Lippi, and Reichlin (2005), SW2: Stock and Watson (2002a,b). EA GDP is Euro Area real GDP. Panel A is based on monthly data and contains results for the level and 6 month %change in CCIs. Panel B is based on quarterly data and contains results for the level and 2 quarters %change in CCIs

TABLE 8. CCIs and EUROCOIN

A: Correlation with Eurocoin

Aggregated CCIs			Pooled dataset			Eurocoin
NMB	FHLR2	SW2	NMB	FHLR2	SW2	
0.777	0.821	0.819	0.761	0.777	0.766	1

B: correlations with EA 1-quarter GDP growth

Aggregated CCIs			Pooled dataset			Eurocoin
NMB	FHLR2	SW2	NMB	FHLR2	SW2	
0.780	0.769	0.773	0.760	0.655	0.704	0.746

The table displays the correlations of our alternative CCIs with the Eurocoin and with Euro Area real GDP growth. Panel A displays correlations of the levels, panel B correlations of the 1-quarter percentage changes. CCIs are: NMB: Non -model-based, FHLR2: Forni, Hallin, Lippi, and Reichlin (2005), SW2: Stock and Watson (2002a,b). Sample 1994:3 -2004:11

TABLE 9. CCIs and ESI

A: Correlations with ESI

Aggregated CCIs			Pooled dataset			ESI
NMB	FHLR2	SW2	NMB	FHLR2	SW2	
0.702	0.621	0.624	0.664	0.558	0.549	

B: Correlations with EA 1-year GDP growth

Aggregated CCIs			Pooled dataset			ESI
NMB	FHLR2	SW2	NMB	FHLR2	SW2	
0.924	0.910	0.906	0.955	0.880	0.878	0.900

The table displays the correlations of our alternative CCIs with the Economic Sentiment Indicator and with Euro Area real GDP growth. Panel A displays correlations of the levels, panel B correlations of the 1-year percentage changes. CCIs are: NMB: Non -model-based, FHLR2: Forni, Hallin, Lippi, and Reichlin (2005), SW2: Stock and Watson (2002a,b). Sample 1994:3 -2004:11

TABLE 10. CCIs and ESI:correlations with individual countries 1-year GDP growth

ESI		**FHLR2**	
France	0.831	France	0.940
Germany	0.837	Germany	0.862
Italy	0.574	Italy	0.904
Spain	0.686	Spain	0.756
NMB		**SW2**	
France	0.954	France	0.882
Germany	0.881	Germany	0.875
Italy	0.725	Italy	0.771
Spain	0.801	Spain	0.794
SW		**Pool**	
France	0.807	France	0.919
Germany	0.830	Germany	0.863
Italy	0.663	Italy	0.882
Spain	0.706	Spain	0.776

The table reports the correlations between the CCis and the annual GDP growth rate. CCIs are: NMB: Non -model-based , SW: Stock and Watson (1989), FHLR2: Forni, Hallin, Lippi, and Reichlin (2005), SW2: Stock and Watson (2002a,b), POOL: pooling of all CCIs. Samples are: France 1970:3-2005:3, Germany 1994:3-2005:3, Spain 1985:1-2005:3, Italy 1980:1-2004:11.

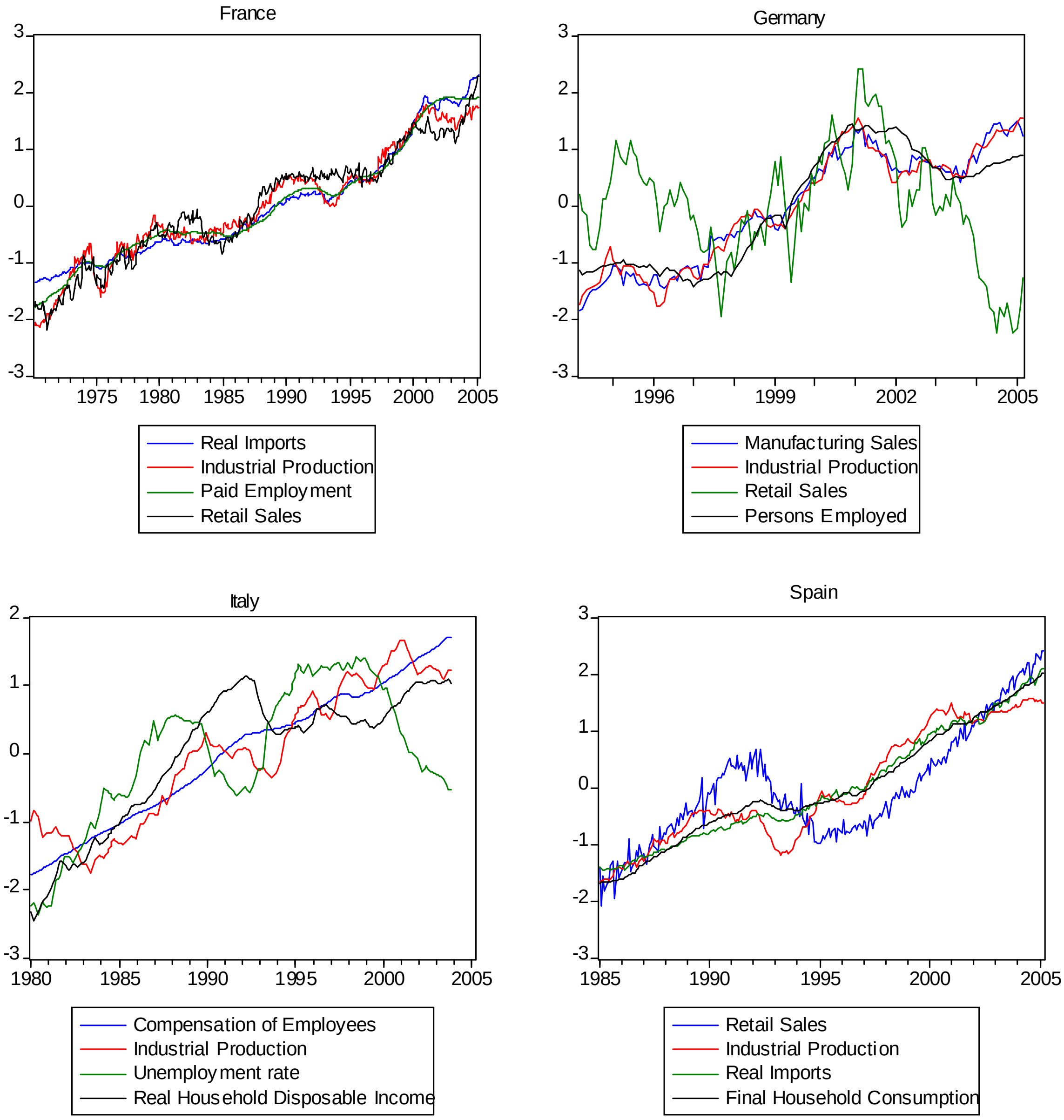

Figure 1: Coincident indexes

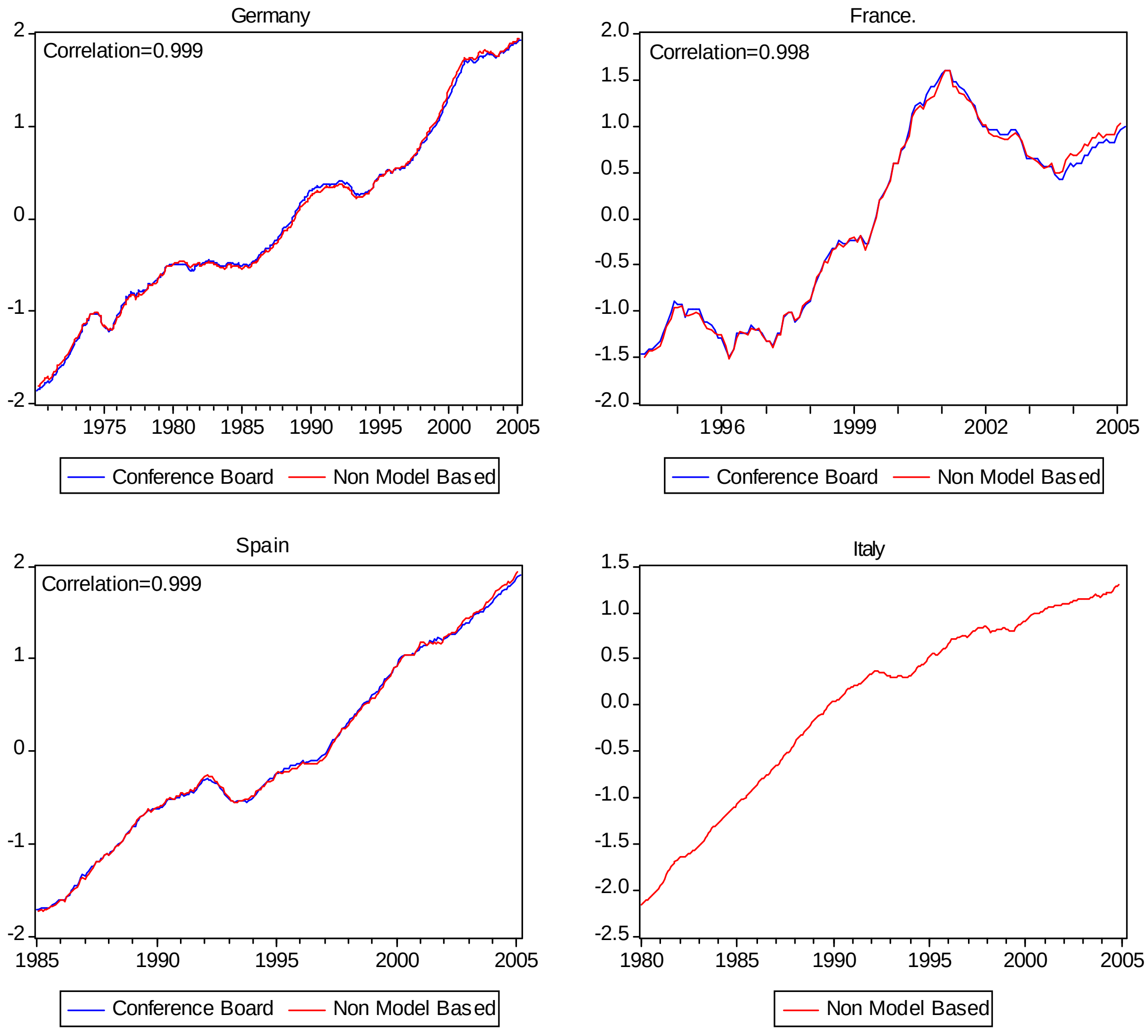

Figure 2: Conference Board indexes and our Non Model Based replicas - Levels

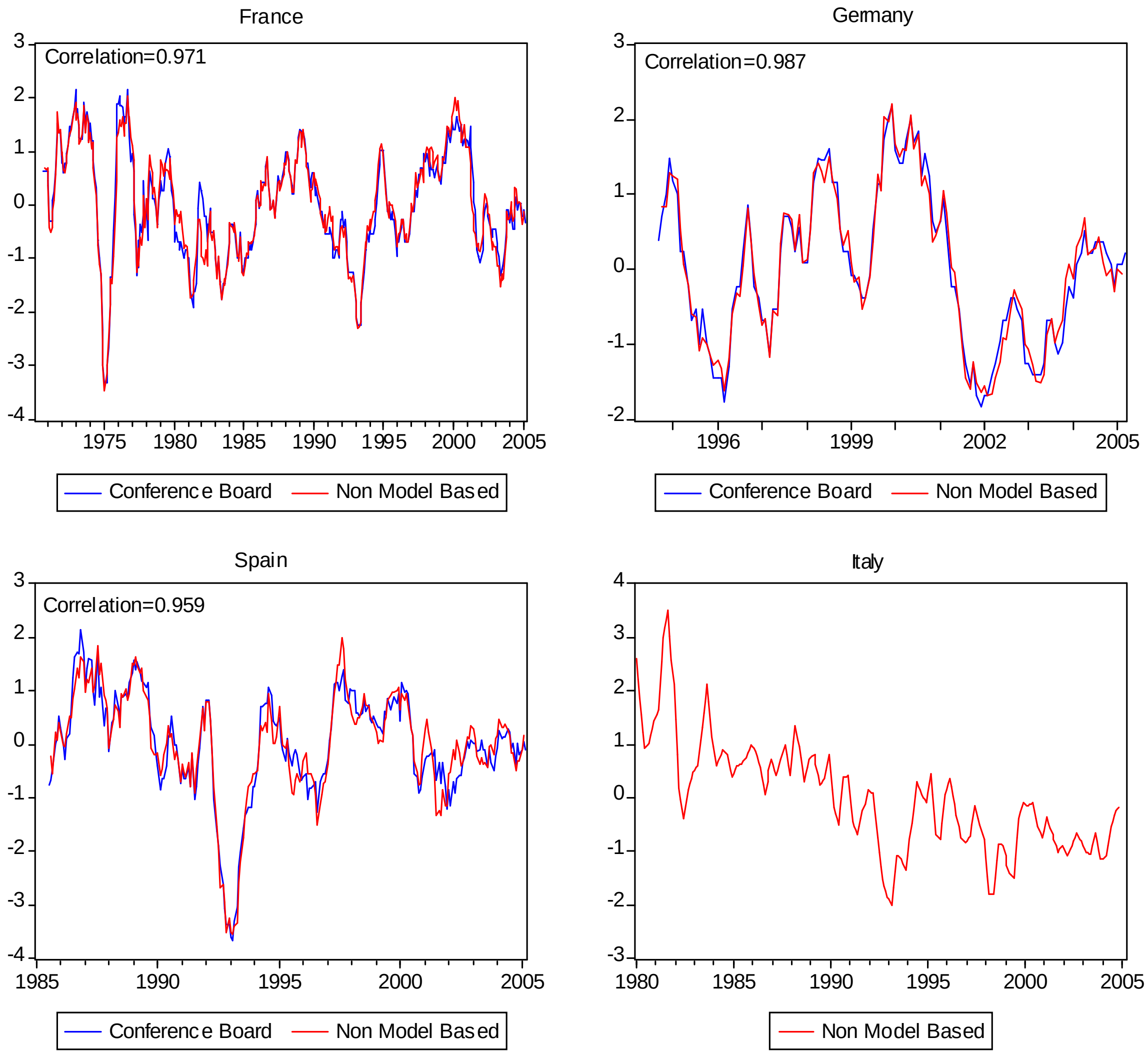

Figure 3: Conference Board indexes and our Non Model Based replicas - 6-month %change

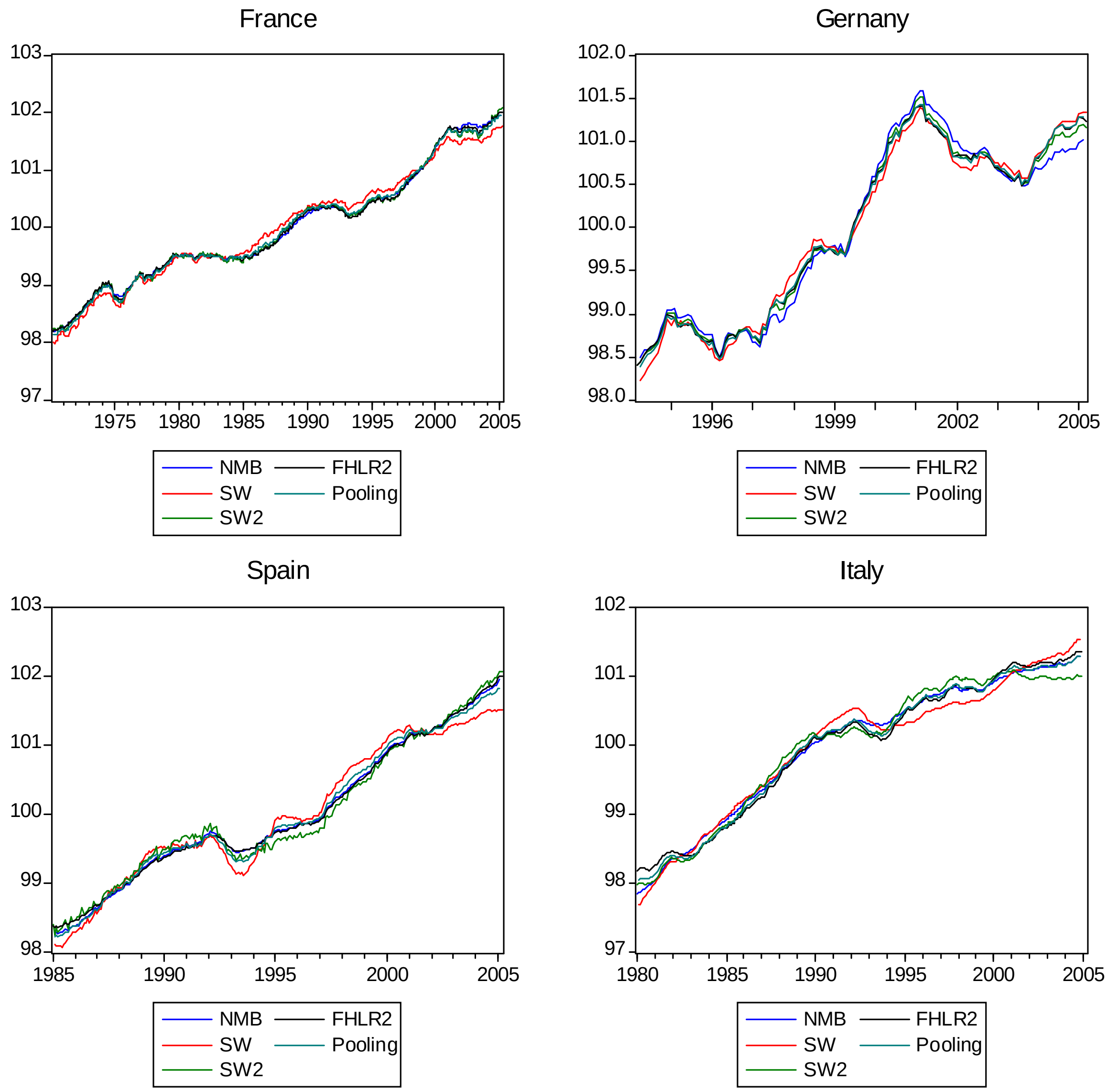

Figure 4: Alternative CCIs for European countries - Levels

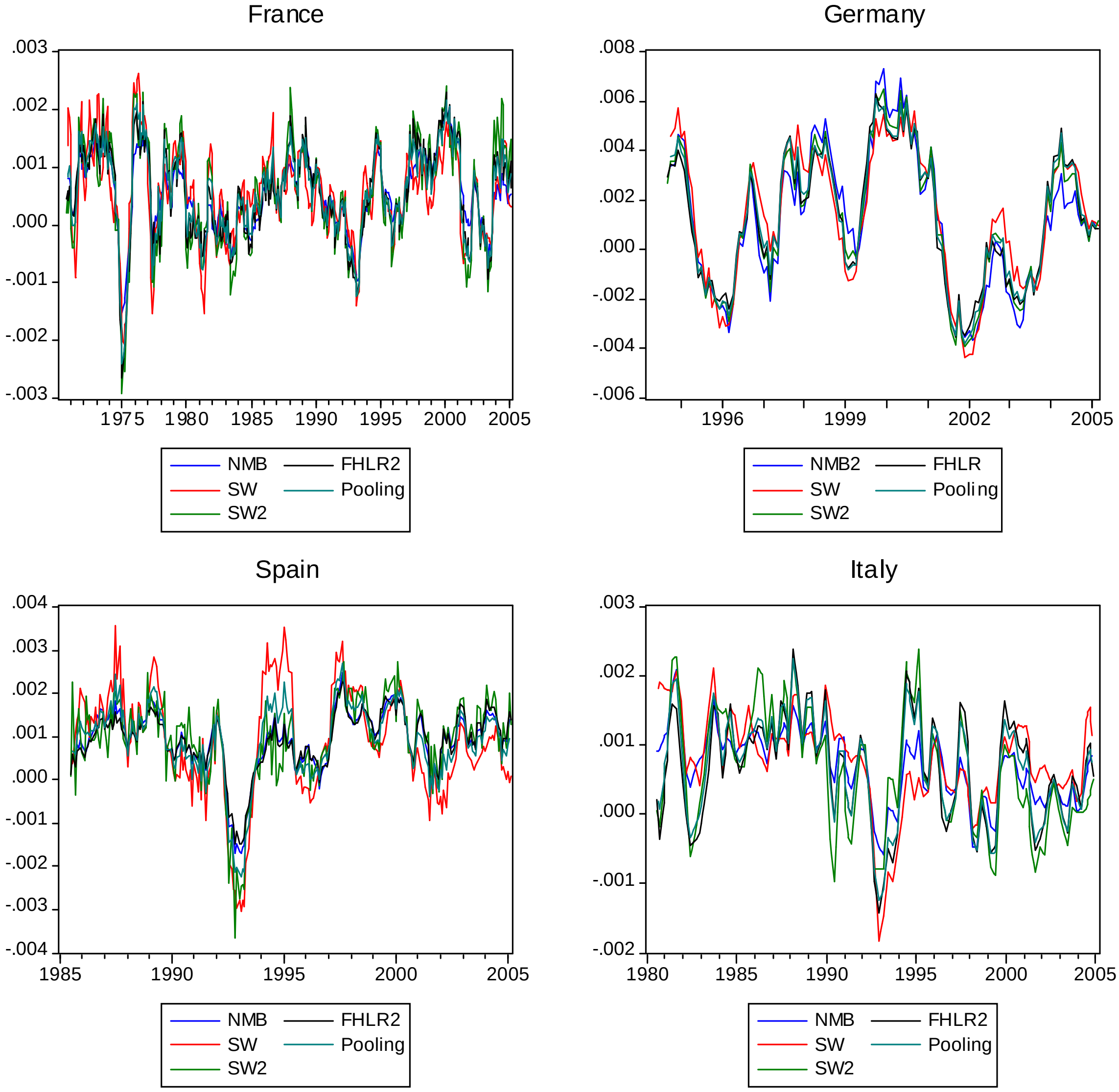

Figure 5: Alternative CCIs for European countries - 6-month %change

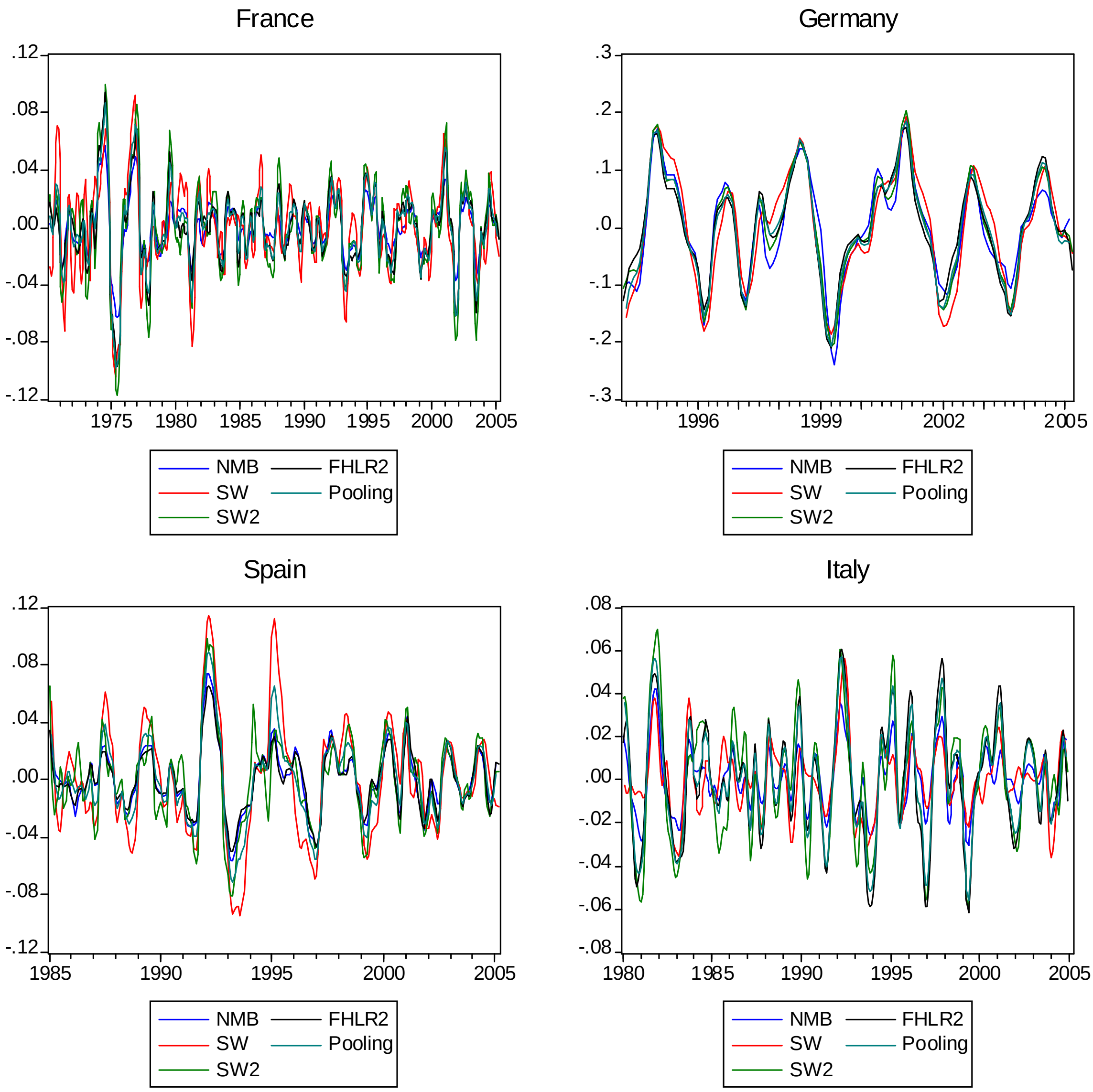

Figure 6: Alternative CCIs for European countries - HP bandpass filtered

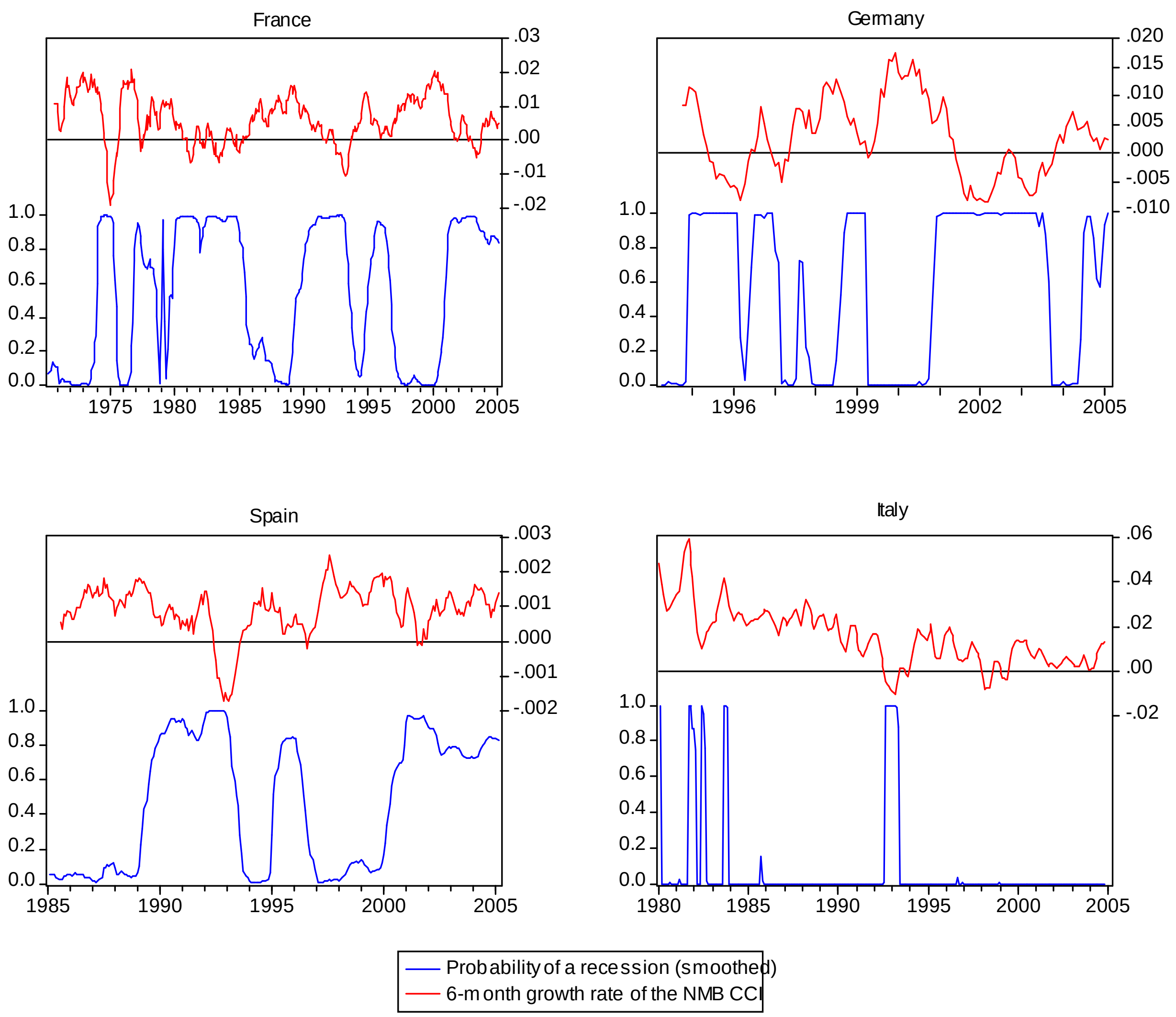

Figure 7: MS-CCI for European countries, smoothed probabilities

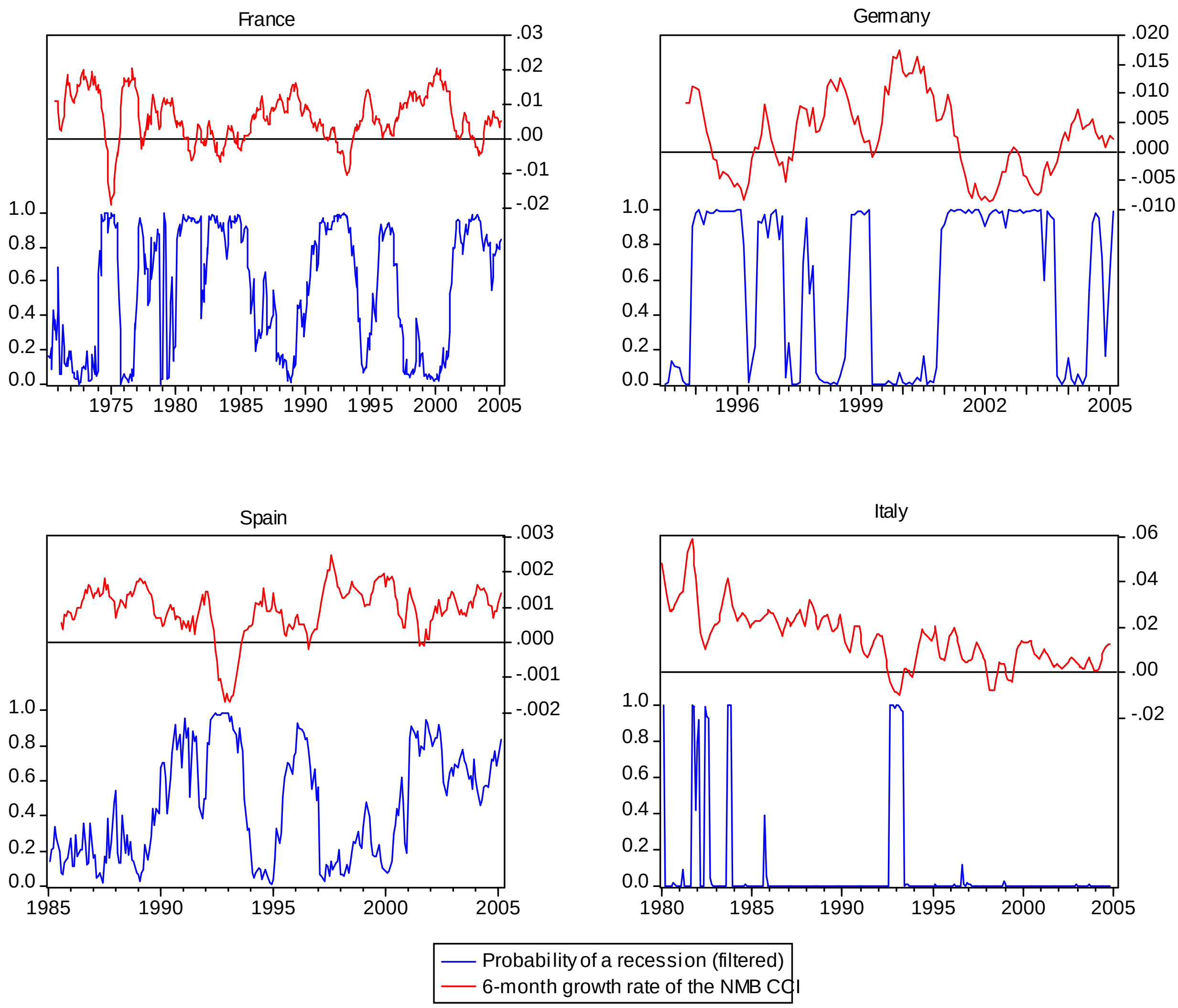

Figure 8: MS-CCI for European countries, filtered probabilities

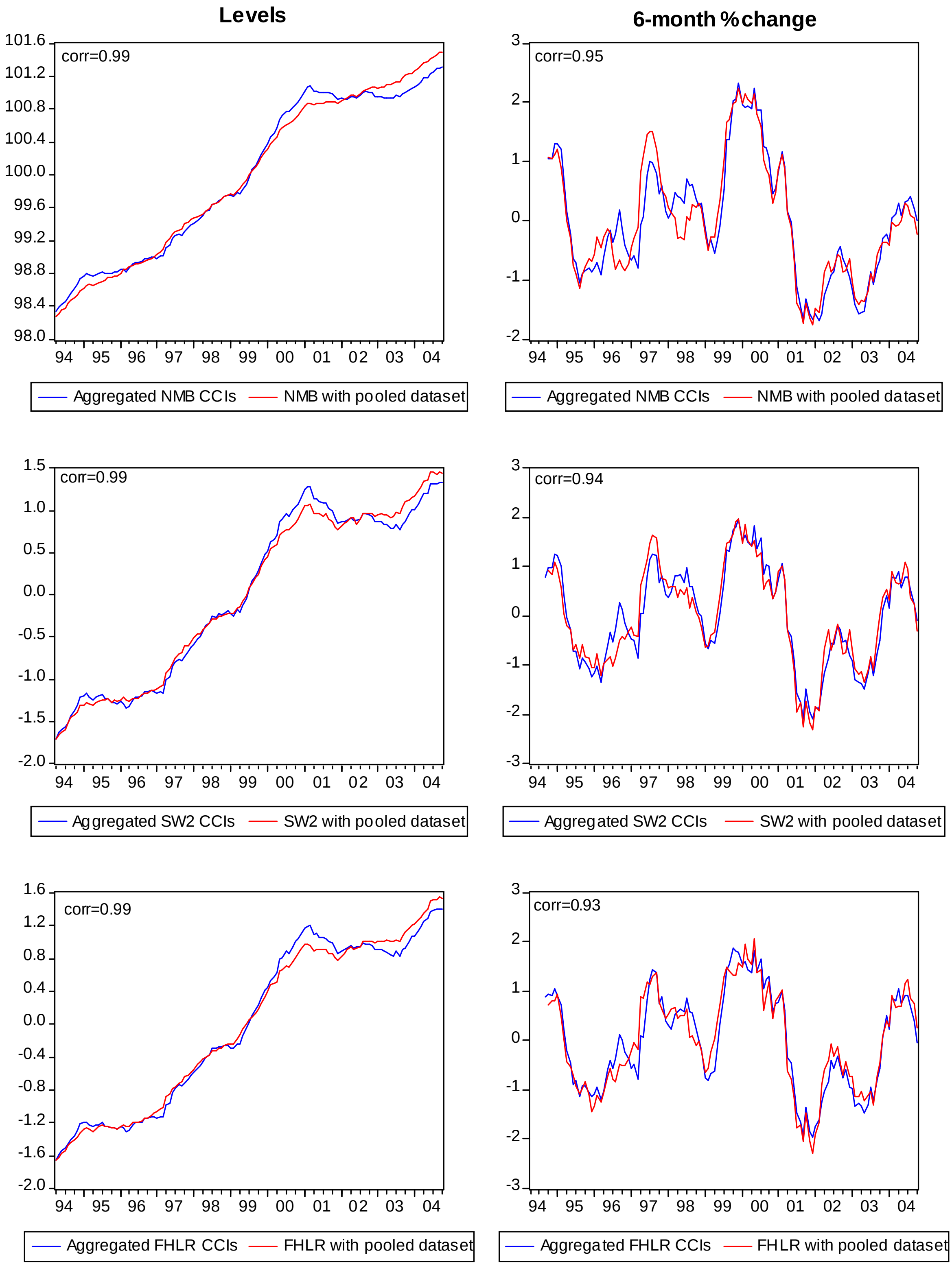

Figure 9: Euro CCIs based on aggregation of national CCIs and on the pooled dataset.

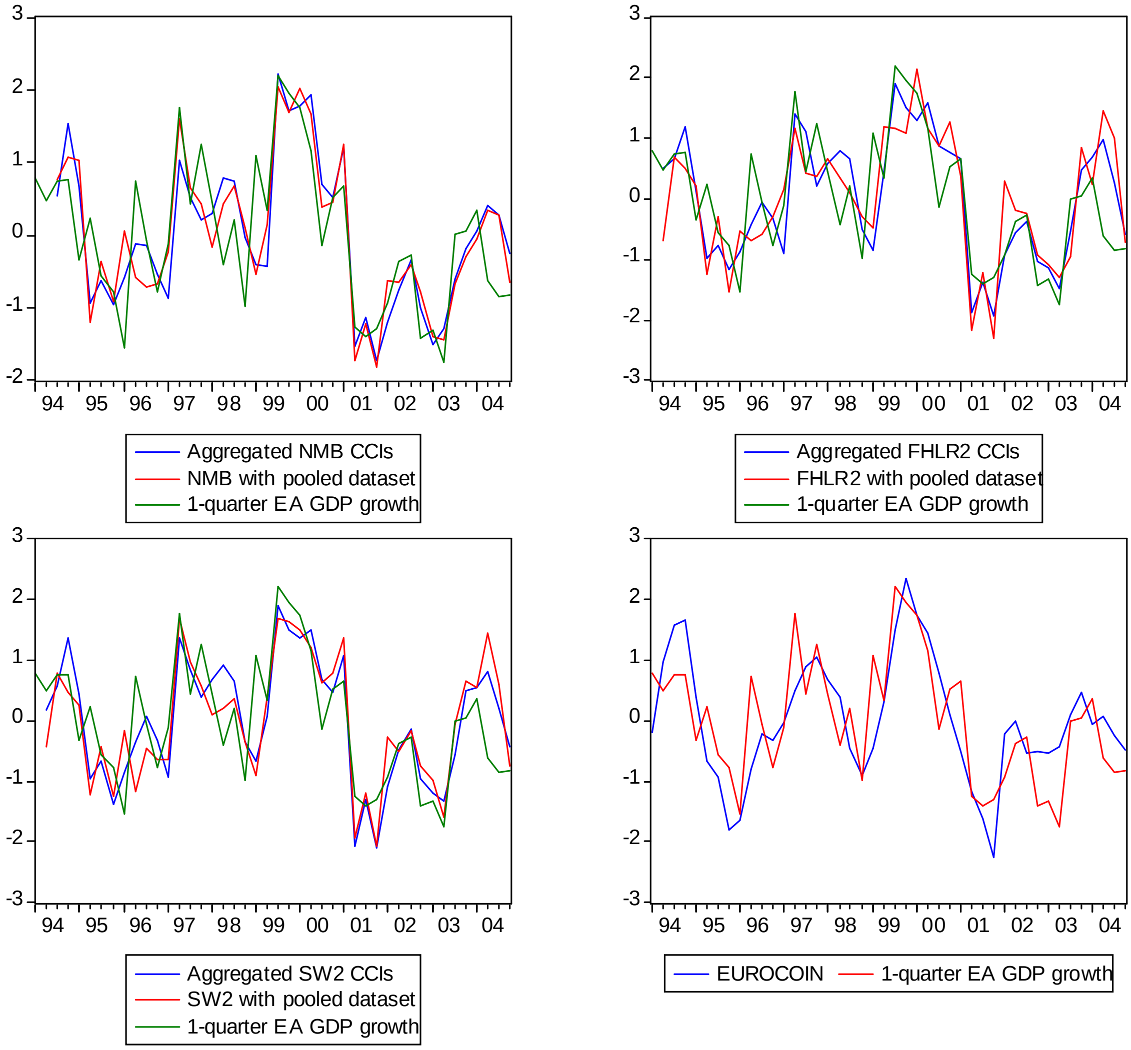

Figure 10: Euro CCIs, Eurocoin, and EA GDP quarterly growth rate

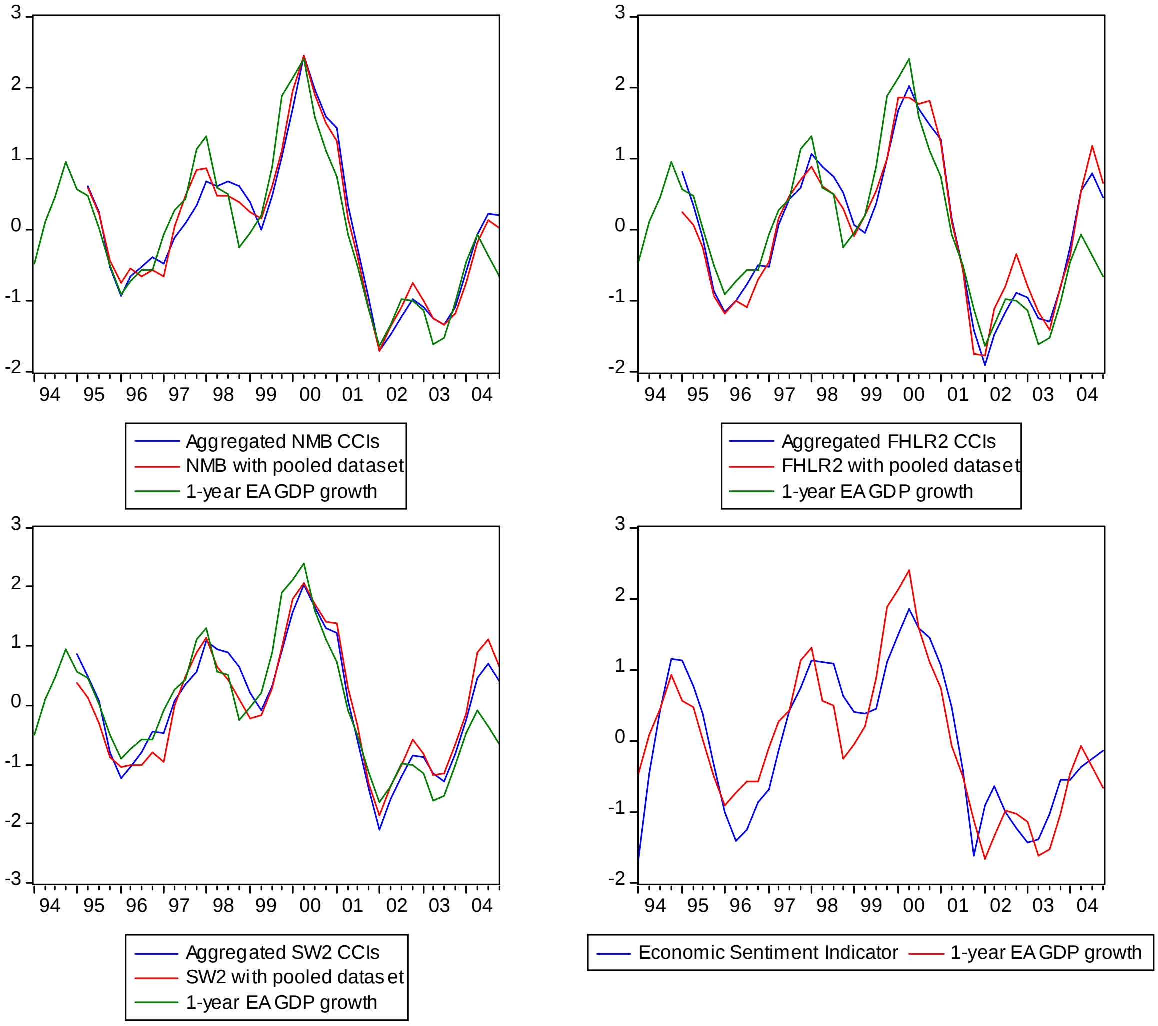

Figure 11: Euro CCIs, Economic Sentiment Indicator, and EA GDP annual growth rate