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A FREQUENCY BAND APPROACH**

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Coincident and leading indicators for the euro area: a frequency band approach

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Abstract

In the context of a common monetary policy, tracking euro area economic developments becomes essential. The aim of this paper is to build monthly coincident and leading composite indicators for the euro area business cycle. However, instead of looking at the overall comovement between the variables as it is standard in the literature, we show how one can resort to both time and frequency domain analysis to achieve additional insight about their relationship. We find that, in general, the lead/lag properties of economic indicators depend on the cycles periodicity. Following a frequency band approach, we take advantage of this in the construction of the coincident and leading composite indicators. The resulting indicators are analysed and a comparison with other composite indicators proposed in the literature is made.

1 Introduction

Since the introduction of the single currency, monetary policy in the euro area is being conducted with reference to the economic developments regarding the entire region rather than any individual country. In this context, it is important to have tools that allow the monitoring of the overall state of euro area economic activity. As pointed out by the European Central Bank (ECB) (2001), composite indicators can be a useful input for economic short-term analysis. The construction of composite indicators is a widely used procedure for synthesizing information on various economic sectors stemming from different sources. Relative to other economy-wide measures such as GDP, they allow a higher frequency assessment of the economic situation due to its monthly nature and they are also more readily available.

The aim of this paper is to construct coincident and leading composite indicators which are able to provide early information regarding current and future euro area business cycle developments, respectively. Once defined the euro area reference business cycle, a wide range of economic indicators (including surveys, industrial production, retail sales, and so on) can be analysed in terms of their lead/lag relationship. Usually, this is done in the time domain. However, one can achieve additional insight about their relationship by resorting to spectral analysis. In particular, as pointed out by Granger and Hatanaka (1964, chapter 6), there is no reason to believe that economic variables should present the same correlation and/or the same lead/lag at all frequencies. Indeed, the results obtained show that this is the case for almost all the indicators analysed here. Therefore, in the construction of the composite indicators, one can exploit this information to select and use the indicators only wherever they exhibit the desired properties in terms of time displacement and comovement. This can be done through band-pass filtering and principal component analysis. Actually, we end up following Schumpeter's (1939) framework, in the sense that we model the euro area business cycle as the sum of long, medium and short cycles. This frequency band approach is specially relevant when building leading composite indicators. In particular, it becomes increasingly more important when the desired time lead increases. Furthermore, the resulting coincident and leading composite indicators are not outperformed by other composite indicators proposed in the literature such as €COIN and Composite Leading Indicator (CLI), which are being regularly released by the Centre for Economic Policy Research (CEPR) and the Organisation for Economic Cooperation and Development (OECD), respectively.

The paper is organised as follows. In section 2, we define the euro area reference business cycle. Section 3 describes some measures of business cycle comovement, both in time and frequency domain, and presents the corresponding results for several euro area economic indicators. The procedure followed in the construction of the coincident and leading composite indicators and a discussion of the results obtained are presented in section 4. In section 5, a comparison with other composite indicators is made. Finally, section 6 concludes. In the appendix, we describe the data used in the paper.

2 The reference business cycle

As a preliminary step for the classification of economic indicators as leading, coincident or lagging, it is necessary to define an euro area reference business cycle. This involves choosing the reference series and it raises the problem of how to isolate the cyclical component of a time series.

2.1 Reference series

Regarding the reference series, the pioneer work on US business cycles developed by Burns and Mitchell (1946) could provide us with a starting point. According to Burns and Mitchell (1946),

“Business cycles are a type of fluctuation found in the aggregate economic activity [...]” (p. 3),

where

“Aggregate activity can be given a definite meaning and made conceptually measurable by identifying it with gross national product [...]” (p. 72).

As stressed by Harding and Pagan (2002), Burns and Mitchell ended up using a wide range of series to define aggregate economic activity instead of a single one, GDP, because the latter was unavailable to them. Nowadays, although available only on a quarterly basis, GDP is undoubtedly the measure of output with the broadest economic coverage and it is used by most policy makers in the assessment of economic developments. Therefore, it seems natural to follow Stock and Watson (1999) who consider that

“[...] fluctuations in aggregate output are at the core of the business cycle so the cyclical component of real GDP is a useful proxy for the overall business cycle and is thus a useful benchmark for comparisons across series.”

2.2 Filtering

In this paper, we focus on growth cycles, i.e., deviations of a series from its long-run trend, in contrast with classical cycles which refer to cycles in the level of a series. A growth cycle is, by definition, a stationary variable.

Thus, for nonstationary time series some kind of stationarity inducing transformation has to be done. Moreover, it is desirable to achieve stationarity without distorting the cyclical properties of the time series.

Since the work of Nelson and Plosser (1982) there has been growing evidence supporting that most economic time series are better modeled as difference stationary than as trend stationary. Therefore, an obvious filtering procedure would be to first difference real GDP, which corresponds to calculate quarterly growth rates when the series is in logarithms. I.e., for the time series y_t , the filtered series, y_t^F , would be

$$y_t^F = (1 - L)y_t \quad (1)$$

where L is the lag operator. In what follows, we consider the treatment of filtering by resorting to frequency domain analysis.

According to the spectral representation theorem, a zero mean stationary series y_t can be expressed as

$$y_t = \int_{-\pi}^{\pi} e^{i\omega t} dZ_y(\omega) \quad (2)$$

where i is the imaginary number, ω is the frequency measured in radians and $dZ_y(\omega)$ is an orthogonal increment process, i.e., a time series can be interpreted as the sum of an infinite number of uncorrelated periodic components.

Suppose that a linear filter $B(L)$,

$$B(L) = \sum_{j=-k}^k b_j L^j \quad (3)$$

has been applied to y_t ,

$$y_t^F = B(L)y_t. \quad (4)$$

Then, the spectral representation of the filtered series is given by

$$y_t^F = \int_{-\pi}^{\pi} e^{i\omega t} B(e^{-i\omega}) dZ_y(\omega). \quad (5)$$

Writing the frequency response function, $B(e^{-i\omega})$, in polar form as

$$B(e^{-i\omega}) = G(\omega)e^{i\phi(\omega)} \quad (6)$$

we can obtain the following result, substituting (6) into (5),

$$y_t^F = \int_{-\pi}^{\pi} e^{i\omega\left(t + \frac{\phi(\omega)}{\omega}\right)} G(\omega) dZ_y(\omega). \quad (7)$$

The effects of a linear filter on the spectral representation are now made clear. The gain, $G(\omega)$, is the factor by which the periodic component of frequency ω , i.e., with periodicity $\frac{2\pi}{\omega}$ time units, is amplified or attenuated. The phase, $\phi(\omega)$, refers to the time displacement in the series induced by the filter. For a given $\phi(\omega)$, the shift in time units is $\frac{\phi(\omega)}{\omega}$. If the filter is symmetric ($b_j = b_{-j}$ for all j) then there is no phase shift. Furthermore, filters whose gain function at $\omega = 0$ is zero can render stationary a time series containing a unit root. By plotting the gain function, one can easily assess the frequency reweighting that is involved when a filter is used, i.e., how the relative importance of the various cyclical components is changed. Figure 1 gives the gain function of several filters¹. The first difference filter reweights heavily in favour of the high-frequency components, i.e. short-run movements, thereby providing a distorted picture of the cyclical component of a series. Moreover, since it is not a symmetric filter it induces a phase shift.

A filter that has been widely used in real business cycle literature is the one proposed by Hodrick and Prescott (1997). As shown by King and Rebelo (1993), when the Hodrick-Prescott filter is applied to an infinite sample yields the following filtered series

$$y_t^F = \left(\frac{\lambda(1-L)^2(1-L^{-1})^2}{1 + \lambda(1-L)^2(1-L^{-1})^2} \right) y_t \quad (8)$$

where λ is the parameter that penalizes the variability in the trend component. Looking at the gain function, one can see that this filter behaves approximately as an ideal high-pass filter which places zero weight below some specified frequency (the cutoff frequency) and unit weight above it. In particular, for $\lambda = 1600$, which is the recommended value by Hodrick and Prescott for quarterly data, the filter passes approximately only components with periodicity less than or equal to 32 quarters. Moreover, since the filter is symmetric there is no phase shift. However, the discussed filter refers to the infinite sample version of the Hodrick-Prescott filter which

¹For easier reading, in this figure, as in others below, the horizontal axis refers to time periods instead of frequencies, i.e., the frequency ω was replaced by its time unit counterpart $\frac{2\pi}{\omega}$ in the horizontal axis label.

corresponds to an infinite two-sided moving average. The feasible filter for a finite sample does not share exactly the same properties of its infinite sample counterpart². In particular, near the endpoints, the filter becomes a one-sided moving average and the gain function differs substantially from the ideal one introducing also a phase shift.

Recently, there has been a growing interest in band-pass filters, i.e., filters capable of retaining the components of a specified frequency band while discarding all the others. The ideal band-pass filter should be able to eliminate completely the frequencies we are not interested in while leaving unaffected the ones of interest, and should not introduce a phase shift. To isolate fluctuations of periodicity between $\frac{2\pi}{\omega_U}$ and $\frac{2\pi}{\omega_L}$ ³, the filtered series should be given by

$$y_t^{F*} = B^*(L)y_t \quad (9)$$

where $B^*(L)$ is the ideal band-pass filter⁴,

$$B^*(L) = \sum_{j=-\infty}^{\infty} b_j^* L^j \quad (10)$$

with the following weights

$$b_0^* = \frac{\omega_U - \omega_L}{\pi} \text{ and } b_j^* = \frac{\sin(j\omega_U) - \sin(j\omega_L)}{\pi j} \text{ for } j \neq 0. \quad (11)$$

However, since the ideal band-pass filter can only be applied to an infinite time series, some approximation has to be used with a finite sample of T observations. Baxter and King (1999) suggest approximating the ideal band-pass filter by considering a finite moving average and choosing the filter weights such that

$$b_j = \min_{j=-K, \dots, K} \int_{-\pi}^{\pi} |B^*(e^{-i\omega}) - B_K(e^{-i\omega})|^2 d\omega \quad (12)$$

²See Baxter and King (1999) for a detailed discussion of the Hodrick-Prescott filter in finite samples.

³As it has been standard in the business cycle literature recently, we will focus on cycles of periodicity between 6 and 32 quarters (see, for example, ECB (2001) for the euro area and Stock and Watson (1999) and Baxter and King (1999) for the US).

⁴See, for example, Priestley (1981, p. 275).

for a given K , which refers to the truncation parameter of the two-sided moving average in (3)⁵. The choice of K involves a trade-off, namely, increasing K allows a better approximation to the ideal filter but it also means losing more observations. For quarterly data, Baxter and King recommend $K = 12$ which implies dropping three years of data at the beginning and end of the sample. The gain function of the resulting symmetric filter is similar to the ideal one. Since this filter also removes the highest frequency components, it produces a filtered series smoother than that obtained with the Hodrick-Prescott filter.

Another approximation to the ideal band-pass filter was proposed by Christiano and Fitzgerald (1999). They suggest estimating y_t^{F*} by y_t^F , a linear function of the available data,

$$y_t^F = B^{p,f}(L)y_t \quad (13)$$

where

$$B^{p,f}(L) = \sum_{j=-f}^p b_j^{p,f} L^j \text{ with } f = T - t, p = t - 1 \quad (14)$$

and selecting the filter weights to make y_t^F as close as possible to y_t^{F*} , in the sense of minimizing the mean square error criteria, i.e.,

$$\min_{b_j^{p,f}, j=-f, \dots, p} E[(y_t^{F*} - y_t^F)^2 | y], \quad y = [y_1, \dots, y_T]. \quad (15)$$

In the frequency domain, it resumes to the following

$$\min_{b_j^{p,f}, j=-f, \dots, p} \int_{-\pi}^{\pi} \left| B^*(e^{-i\omega}) - B^{p,f}(e^{-i\omega}) \right|^2 f_y(\omega) d\omega \quad (16)$$

where $f_y(\omega)$ is the spectrum of y_t at frequency ω , which measures the contribution of each frequency component to the overall variance of y_t ⁶. As seen earlier, it is not possible to obtain $B^*(e^{-i\omega}) = B^{p,f}(e^{-i\omega})$ for all ω with finite p and f , but as pointed out by Christiano and Fitzgerald the two functions can be made similar over some intervals by sacrificing accuracy

⁵Additionally, it is imposed that the filter weights sum to zero in order to obtain a filter that places zero weight at the zero frequency.

⁶As in the Baxter-King band-pass filter, it is also imposed the constraint that the filter weights sum to zero.

over other intervals. Thus, $f_y(\omega)$ can be interpreted as the implicit weighting scheme that determines which intervals to emphasize. Obviously, this requires the knowledge of the true time series representation of y_t , which is of course unknown. Instead of estimating it, Christiano and Fitzgerald suggest proceeding as the data had been generated by a random walk (see Figure 2⁷). Not surprisingly, this turns out to work quite well for standard macroeconomic time series since many of them have what Granger (1966) called the “typical spectral shape” of an economic variable, with low frequencies dominating the spectrum. The resulting filter is non-stationary, i.e., p and f vary with t , and it is not symmetric. Note that, if stationarity and symmetry were imposed, $p = f = K$ with K fixed, and equal weight was assigned to all frequencies, $f_y(\omega) = 1$, then (16) would collapse into (12). Taking $p = f = K$ one can evaluate the consequences of the weighting scheme by the comparison of the resulting gain function with the one corresponding to the Baxter-King filter (see Figure 1). As expected, since the weighting scheme emphasizes the components with higher periodicity, the gain function is closer to the ideal one at low frequencies at the cost of performing worse at higher frequencies. Regarding non-stationarity and asymmetry, Christiano and Fitzgerald found that they were valuable in the minimization problem since they allowed to increase the amount of information in y_t that could be used in estimating y_t^F . Moreover, they also found that the phase shift was negligible and that there was little gain in knowing the true time series representation of y_t . Therefore, as noted by Christiano and Fitzgerald, proceeding as if the data had been generated by a random walk and using filters that are optimal in that case can be considered a nearly optimal procedure to isolate frequency bands in macroeconomic time series⁸. Another attractive feature of the Christiano-Fitzgerald filter is that, in contrast with the Baxter-King filter, there is no loss of data from filtering, i.e., it can be used to obtain real-time estimates of the cyclical component. Furthermore, they have shown that their filter outperforms the Hodrick-Prescott filter in this context. Thus, we will use the Christiano-Fitzgerald band-pass filter to isolate the desired cycles.

⁷ *Pseudo*-spectrum because the process is non-stationary (see Harvey (1990, p. 60)).

⁸Their finding is valid for both difference and trend stationary series.

3 Analysis of business cycle comovements

In this section, we describe some measures of business cycle comovement, both in time and frequency domain, and present the corresponding results for several euro area economic indicators.

3.1 Comovement measures

Traditionally, the analysis of the comovements between any two variables is done in the time domain, namely, by analysing the cross-correlogram. The cross-correlation function, $\rho_{xy,\tau}$ ⁹, is a measure of the degree to which two variables move together at different time lags. Its sign tells us if they move in the same or opposite directions and its absolute value measures the strength of the comovement. It is also used to assess if movements in one variable tend to occur or not at the same time as movements in another variable. When measured contemporaneously ($\tau = 0$) it provides a measure of how much they move together at the same time. The lead/lag relationship is established based on the value of τ for which the absolute cross-correlation function is maximized. Thus, the cross-correlogram analysis can provide us a useful description of the overall relationship between variables.

However, one can use frequency domain analysis to characterize the comovement between the variables frequency by frequency. Let us consider the multivariate spectrum $F_{\{x_t, y_t\}}(\omega)$ for a bivariate zero mean covariance stationary process $\{x_t, y_t\}$, which is the frequency domain analogue of the autocovariance matrix. The diagonal elements of $F_{\{x_t, y_t\}}(\omega)$ are the spectrum of the individual processes and the off-diagonal elements refer to the cross-spectrum. Since the cross-spectrum between x_t and y_t is, in general, complex valued, it can be decomposed into imaginary and real parts and written as

$$f_{xy}(\omega) = c_{xy}(\omega) - iq_{xy}(\omega) \quad (17)$$

where $c_{xy}(\omega)$ is the co-spectrum and $q_{xy}(\omega)$ is the quadrature spectrum. Two well known frequency domain measures of comovement are the coherency, $C_{xy}(\omega)$, and the phase, $\phi_{xy}(\omega)$. The coherency is given by

⁹Defined here as $\rho_{xy,\tau} = \frac{\text{cov}(x_t, y_{t+\tau})}{\sqrt{\text{var}(x_t)\text{var}(y_t)}}$.

$$C_{xy}(\omega) = \frac{|f_{xy}(\omega)|}{\sqrt{f_x(\omega)f_y(\omega)}}, \quad 0 \leq C_{xy}(\omega) \leq 1 \quad (18)$$

and measures the absolute correlation between x_t and y_t at frequency ω . A higher value of $C_{xy}(\omega)$ implies a higher correlation between the two time series at frequency ω . However, this measure is invariant to the time position of the series, i.e., shifting a series over time does not affect $C_{xy}(\omega)$. Thus, although it provides knowledge about the extent to which x_t and y_t are related at frequency ω it does not give any information about how much they are out of phase. For that assessment we have to use the following measure

$$\phi_{xy}(\omega) = \tan^{-1} \left(-\frac{q_{xy}(\omega)}{c_{xy}(\omega)} \right). \quad (19)$$

If the phase is positive then x_t lags y_t at frequency ω . If the phase is negative then x_t leads y_t at frequency ω . I.e., the time delay of y_t at frequency ω is given by $-\frac{\phi_{xy}(\omega)}{\omega}$ which is not necessarily an integer. Therefore, the phase tells us which series is leading and by how many periods.

So, one can use the above measures to characterize the lead/lag relationship between x_t and y_t , frequency by frequency, in the same way as it would be done with the cross-correlogram since, as pointed out by Fishman (1969, p. 65), the absolute correlation between two variables at frequency ω is maximized when the phase shift is given by (19) with the maximum given by (18).

Nevertheless, one might be particularly interested in measuring the contemporaneous comovement of the variables at frequency ω . For that, one has to resort to the measure proposed by Croux *et al.* (2001), the dynamic correlation, which is defined as

$$\rho_{xy,0}(\omega) = \frac{c_{xy}(\omega)}{\sqrt{f_x(\omega)f_y(\omega)}}. \quad (20)$$

This measure is no more than the contemporaneous correlation between x_t and y_t at frequency ω .

All these measures can provide us the relevant information through appealing graphics when plotted against the frequency axis. However, when one wants to compare those statistics across many time series, some sort of feasible procedure has to be adopted. Instead of looking at a continuum of

frequencies one could pick out some frequencies arbitrarily¹⁰ or better, one could focus on a limited number of frequency bands encompassing the entire frequency range of interest. Croux *et al.* (2001) provided the frequency band counterpart of their measure. Thus, one only needs to obtain the same kind of information of the other two measures for a frequency band.

For a given frequency band Λ ¹¹, we can define the covariance between x_t and y_t within Λ as

$$\text{cov}_\Lambda(x_t, y_{t+\tau}) = \int_\Lambda e^{i\omega\tau} f_{xy}(\omega) d\omega \quad (21)$$

and the variances as

$$\text{var}_\Lambda(x_t) = \int_\Lambda f_x(\omega) d\omega \quad (22)$$

$$\text{var}_\Lambda(y_t) = \int_\Lambda f_y(\omega) d\omega. \quad (23)$$

Then, one can define the cross-correlation between x_t and y_t within the frequency band Λ as

$$\rho_{xy,\tau}(\Lambda) = \frac{\int_\Lambda e^{i\omega\tau} f_{xy}(\omega) d\omega}{\sqrt{\int_\Lambda f_x(\omega) d\omega \int_\Lambda f_y(\omega) d\omega}}. \quad (24)$$

Therefore, an obvious procedure to identify the lead/lag relationship between x_t and y_t at the frequency band Λ would be to choose τ so as to maximize the absolute value of $\rho_{xy,\tau}(\Lambda)$. As expected, when $\tau = 0$, (24) collapses into the frequency band counterpart of dynamic correlation, which is nothing else than the contemporaneous correlation between x_t and y_t at the frequency band Λ . Now, to see how $\rho_{xy,\tau}(\Lambda)$ is related to coherency and phase consider $f_{xy}(\omega)$ in the polar form,

$$f_{xy}(\omega) = |f_{xy}(\omega)| e^{i\phi_{xy}(\omega)}. \quad (25)$$

Substituting (25) into (24), and after some algebraic manipulations, yields the following

¹⁰For example, Forni *et al.* (2001) classified the series as leading, coincident or lagging according to their phase at a typical business cycle frequency, namely, $\frac{\pi}{16}$, corresponding to a cycle of periodicity of eight years.

¹¹Following Croux *et al.* (2001), $\Lambda = \Lambda_+ \cup \Lambda_-$ with $\Lambda_+ = [\lambda_1, \lambda_2)$, $\Lambda_- = [-\lambda_2, -\lambda_1)$ and $0 \leq \lambda_1 < \lambda_2 \leq \pi$.

$$\rho_{xy,\tau}(\Lambda) = \frac{\int_{\Lambda} e^{i\omega\left[\tau - \left(-\frac{\phi_{xy}(\omega)}{\omega}\right)\right]} |f_{xy}(\omega)| d\omega}{\sqrt{\int_{\Lambda} f_x(\omega) d\omega \int_{\Lambda} f_y(\omega) d\omega}}. \quad (26)$$

Let us focus on the single frequency case, i.e, suppose that Λ contains only the frequency ω . Then, searching for τ that maximizes the absolute value of (26) corresponds to setting τ equal to the time delay, since by definition coherency is the maximum correlation between the two variables at frequency ω . Hence, the suggested procedure, when applied to the single frequency case, yields the phase and the coherency.

Alternatively, one could characterise the comovements between the variables in a particular frequency band by isolating the components belonging to that frequency band through a band-pass filter and then calculating the corresponding cross-correlations¹². While the first method avoids the problems associated with band-pass filtering¹³ and offers additional precision in terms of lead/lag determination due to its non-integer possibility¹⁴, its application raises issues related with spectrum and cross-spectrum estimation. Although similar results should be expected, in practice those procedures might lead to different conclusions. Therefore, as it will be done in the next section, both methods can be used to assess the robustness of the findings.

3.2 Empirical results

Once established the operational framework to characterise the comovements, we proceed into the empirical analysis of the relationship between the cyclical components of euro area GDP and several economic indicators (surveys, industrial production, retail sales, monetary aggregates, interest rates, stock prices, among others) from 1987 to 2001^{15,16}.

Accordingly, we consider a limited number of frequency bands comprising the standard business cycle frequency range, from 6 to 32 quarters. In particular, we focus on three frequency bands, namely, long cycles (of peri-

¹²For a similar point see Croux *et al.* (2001) when discussing their measure.

¹³However, it requires stationarity of the series.

¹⁴This can be a significant advantage when analysing economic phenomena that are recorded with a substantial time interval.

¹⁵See the appendix for a detailed description of the data.

¹⁶Note that, all the indicators considered here are available, for any given quarter, before GDP is released.

odicity between 20 and 32 quarters), medium cycles (from 12 to 20 quarters) and short cycles (from 6 to 12 quarters). This partition is suggested by the spectrum analysis of the GDP cyclical component (see Figure 3)¹⁷. The frequency bands corresponding to long and medium cycles delimit the two major peaks in the spectrum while the remaining peaks are included in the short cycles' frequency band. Regarding the estimation of the spectrum, it was done using a prewhitening technique, which can be particularly useful when working with small samples, as it is our case¹⁸. It consists in applying a certain preliminary transformation to the series prior to spectral estimation in order to improve the accuracy of spectral estimates. In particular, an AR model of order p is fitted to the series and the spectrum of the resulting residuals is estimated by standard methods. Then, the spectrum of the series is obtained by applying the inverse transformation of the $AR(p)$ to the spectrum of the residuals¹⁹.

Although the indicators considered here are available monthly, the comovement analysis is made on a quarterly basis due to GDP availability. Taking into account the nature of the indicators we are working with, it seems reasonable to limit our search for the corresponding maximum absolute cross-correlation to a range between a lag of two quarters and a lead of six quarters²⁰. Besides the maximum absolute cross-correlation and associated lead/lag²¹, we also compute the contemporaneous cross-correlation, which can be particularly useful when analysing coincident indicators, and we also present these statistics for the standard business cycle frequency range as a whole.

The results obtained using the frequency domain approach are presented

¹⁷We only present the spectrum for the standard business cycle frequency range.

¹⁸See, for example, Fishman (1969, chapter 3) for a detailed discussion of the prewhitening technique.

¹⁹We set $p = 10$, as suggested by several information criteria, and used a Parzen lag window with lag truncation parameter equal to $\sqrt[3]{T}$ for the residuals spectrum estimation. The results obtained are not sensitive to the lag window or lag truncation.

²⁰Obviously, whenever it was not possible to find a maximum inside this range we had to enlarge it. This occurred only in a very limited number of cases. This procedure was adopted in order to avoid finding spurious results stemming from the fact that whenever the duration of the business cycles is short, as in Europe, a variable that leads the reference cycle by several months can easily be classified as lagging since it can be closer to the previous cycle than to the next (see Altissimo *et al.* (2001) for a similar point).

²¹For a few variables, we also present another local absolute cross-correlation maximum whenever it could be interesting in terms of leading properties.

in Table 1. As pointed out earlier, this approach involves the estimation of the multivariate spectrum. The multivariate spectrum was also estimated using the prewhitening technique. In the multivariate case, a low-order *VAR* is fitted to the series prior to spectral estimation²².

The results obtained by first isolating each frequency band component with the chosen band-pass filter and then calculating the corresponding cross-correlations are presented in Table 2.

Overall, the analysis of both tables suggests two findings. First, the results obtained with the two different methods lead, in general, to the same conclusions. Second, the variables analysed only seldom present the same cross-correlation and/or the same lead/lag over the entire standard business cycle frequency range.

Business and consumer surveys provide information regarding economic agents' (households and enterprises) assessment of the current economic situation and their intentions or expectations for the future. Therefore, surveys are expected to present coincident or leading characteristics. The manufacturing survey provides information well correlated and with a significant lead, in particular, at long cycles. Regarding short cycles, it gives coincident signals, which is a property shared by all the other surveys. Only the question related with the assessment of stocks is countercyclical. The construction survey presents similar characteristics, although with a shorter lead at long cycles and a slightly longer one at medium cycles while the retail trade survey seems to be, in general, coincident and less correlated, in particular, in short-cycles. Regarding the consumer survey, the results vary more across the different questions, but those related with the financial situation of households and general economic situation seem to be the most informative about business cycle developments. The question related with unemployment expectations is clearly countercyclical.

Both retail sales and car registrations present a procyclical behaviour and appear to lag at long cycles, although only slightly in the first case. At medium cycles, they are coincident and strongly correlated while in short cycles they present a lower comovement, in particular, the retail sales.

All the industrial production indices present a similar pattern, i.e., procyclical and strongly correlated while, in general, coincident at all frequency

²²In particular, we estimated a *VAR*(4) and resorted to the previously used lag window and lag truncation for the residuals multivariate spectrum estimation.

bands. Nevertheless, the industrial production of consumer goods reveals a lag at long cycles and the industrial production of intermediate goods is slightly leading at medium cycles.

Not surprisingly, unemployment is countercyclical and lagging with a high correlation over the entire business cycle frequency range.

Regarding monetary aggregates, we considered M1 and a broader aggregate, M3, both nominal and real. The results obtained for M1 are in line with the widespread idea that M1 is procyclical and a leading indicator for the euro area business cycle. This appears to be particularly true at medium cycles, where there is a strong comovement. Relatively to M3, no such clear conclusions can be drawn from our results. Nevertheless, it seems that M3 can be used as a long leading indicator²³ though less correlated than M1. Concerning the distinction between nominal and real measures, the difference appears to be, in general, negligible, although it has been found elsewhere that real measures have a better predictive content than the nominal ones²⁴.

We also assessed the behaviour of several interest rates over the business cycle. The nominal interest rates, in particular the long-term one, appear to be, in general, procyclical and coincident or lagging. In accordance with the well known link to economic decisions (as, for example, investment ones), the real short-term interest rate seems to be particularly suitable as a countercyclical leading indicator. The interest rate spread, which has been widely recognized as a forward-looking indicator for real activity, is procyclical and it has good leading characteristics, in particular, at medium cycles.

The real effective exchange rate, which is an indicator of the competitiveness of euro area exporters, was also considered. As expected, it was found that an appreciation is followed by a cyclical decline in output. Moreover, it appears to be a quite good leading indicator for short cycles.

Regarding stock prices, since they reflect market participants' expectations about the future state of the economy, they can be a potential source of leading indicators. Therefore, we analysed stock market indices for various economic sectors. Overall, stock market fluctuations are procyclical and leading²⁵. However, at long cycles they are poorly correlated with the refer-

²³As discussed by Altissimo *et al.* (2001).

²⁴See, for example, Altissimo *et al.* (2001) for the euro area and Stock and Watson (1999) for the US.

²⁵In line with the findings of Altissimo *et al.* (2001) for the euro area and Stock and

ence cycle (with the basic materials stock price index being an exception). At medium cycles, stock prices present a strong comovement and a long lead while they are only slightly leading at short cycles.

4 Composite coincident and leading indicators

After obtaining empirical evidence supporting that the comovement characteristics of the economic indicators vary across frequency bands, the next step is to exploit this information in the construction of the composite indicators. Several questions have to be addressed. First, one has to be able to isolate each frequency band component of each indicator. This problem was already solved in the previous section when we resorted to the band-pass filter to study the lead/lag relationship at a particular frequency band. Once isolated the frequency band component of interest, one has to synthesize the information coming from the different variables into a single indicator. A standard statistical technique for summarizing data is the principal component analysis²⁶. It consists in transforming the original N variables into a new set of uncorrelated variables, the principal components. The principal components are linear combinations of the original variables and are obtained such that the first component accounts for the largest possible amount of variation in the original data, the second for the largest possible amount of variation not already accounted by the first one, and so on. The main idea underlying this procedure is to synthesize, non-parametrically, the information contained in the original set of variables with the smallest possible number of components. In practice, whenever the first principal component captures a high proportion of the total variance, as in our case, it can be used as a suitable representation of the original data. Hence, the first principal component will be used to compile at each frequency band the selected indicators by weighting their corresponding frequency band components,

$$z_{\Lambda t} = \alpha_{\Lambda 1} y_{\Lambda 1 t} + \alpha_{\Lambda 2} y_{\Lambda 2 t} + \dots + \alpha_{\Lambda N} y_{\Lambda N t}. \quad (27)$$

where the α 's are the weights that maximize its information content.

Watson (1999) for the US.

²⁶See, for example, Johnson and Wichern (1992).

Now, we focus on the construction of the coincident and leading composite indicators for the euro area. Regarding the leading indicators, we further distinguish between short-leading and long-leading, as suggested by Moore (1991), in order to exploit the fact that some variables present a higher lead time than others. In particular, looking at Tables 1 and 2 there seems to be some clustering around the leads of 2 and 4 quarters, so we build the short and long-leading indicators around them, respectively. For each frequency band we pick those variables that present the strongest comovement and the desired time displacement. In the selection procedure, we also attempt to achieve a balanced composition of the resulting composite indicators by avoiding overweighting some particular economic sector at each frequency band while diversifying the type of indicators used²⁷. Moreover, we check if the inclusion of a given indicator into the composite one is supported by the results obtained with both methods presented in the previous section. In Table 3, we present the variables selected for each frequency band (long, medium and short cycles) of each composite indicator (coincident, short-leading and long-leading). Note that their composition varies across frequency bands since a variable that presents the desired comovement characteristics at some frequency band may not have the same properties at the others.

After selecting the variables, we isolate the frequency band component of interest of each monthly series²⁸ and standardize it. We then compute the first principal component at each frequency band. Table 3 presents the weights obtained for each variable at each frequency band²⁹. One can see that the weights are similar across variables at each frequency band and that the first principal component accounts for a large proportion of the total variance in the data.

However, the resulting first principal component has no meaningful scale and in the aggregation we have to take into account that some cycles are relatively more important than others for the overall business cycle devel-

²⁷Regarding the surveys, whenever possible, we use the sector confidence indicators. However, this is made conditional on the assessment that all the questions belonging to a particular sector confidence indicator possess the desired properties.

²⁸When working with monthly data, the long cycles refer to fluctuations between 60 and 96 months, medium cycles to the ones between 36 and 60 months and the short cycles to fluctuations between 18 and 36 months.

²⁹For presentation purposes, the weights are normalised such that their sum is one.

opments. Therefore, each first principal component is rescaled such that its quarterly average has the same mean and standard deviation as the corresponding frequency band component of GDP. Afterwards, by summation of the components regarding long, medium and short cycles, we obtain the composite indicator for the euro area business cycle. The resulting monthly composite indicators are plotted in Figure 4.

We now assess how these composite indicators track euro area business cycle developments. We follow the same approach as in the previous section to evaluate the comovements at each frequency band. Again, the analysis is done on a quarterly basis. The results are presented in Table 4. One can see that the coincident, short-leading and long-leading indicators have roughly the desired time displacement at each frequency band and present an overall strong comovement with the reference cycle. Note that even for the long-leading indicator (with a time lead of 4 quarters, i.e., a whole year) it was possible to obtain noteworthy results.

In practice, the composite indicators are subject to revisions over time due to data revisions and to their re-computation when new data becomes available. Although it is not possible to assess the consequences of the first potential source of revisions, due to the lack of data vintages, one would expect its impact to be small, since the majority of the series used in the composite indicators are not (such as, interest rates and stock indices) or very little revised (business and consumers' surveys). Moreover, the data revisions that are due to seasonal adjustment should also not influence the composite indicators since we discarded the seasonal frequencies in their construction. Since we cannot take into account the data revisions, the computation of the composite indicators at each period t , using only the data up to and including that period, provides quasi-real estimates (according to Orphanides and van Norden (1999) definition)³⁰. The difference between final and quasi-real estimates allows to assess the importance of the revisions stemming from filtering as well as from principal component analysis and corresponding rescaling procedure. Furthermore, one can disentangle their effects by computing quasi-final estimates. These estimates are obtained in a similar fashion as quasi-real but instead of using the parameter estimates based on the available data at each moment, one uses the full sample parameter estimates, i.e., the same ones used in the final composite indicators.

³⁰We started computing quasi-real estimates after six years of monthly data.

Therefore, the difference between final and quasi-final estimates is due to filtering while the difference between the quasi-final and quasi-real estimates is attributed to parameters' revision. We also assess how these estimates for a given t evolve over time when new data becomes available. At each period t , we have the first estimate for t , the second estimate for $t - 1$, the third estimate for $t - 2$, and so on³¹. Therefore, one can collect the observations corresponding to a particular estimate and assess how reliable it is³². Following Christiano and Fitzgerald (1999), we use three statistics to quantify the importance of the revisions. Namely, we compute the correlation of each estimate with the final one. This would equal one if there were no revisions. We also consider the noise-to-signal ratio, which is the ratio of the standard deviation of the revisions to the standard deviation of the final estimate. In the case of no revisions, this measure would be zero. A value equal or higher than one implies that one can do as well or better by simply using as estimate the mean of the composite indicator. Since the previous two measures are scale invariant, we also present the standard deviation of the revisions to assess its absolute size.

The results are plotted in Figures 5, 6 and 7, respectively. Through the comparison of quasi-real (the bold lines in the figures) with quasi-final estimates (the thin lines in the figures), one can conclude, not surprisingly, that the main source of uncertainty is due to filtering. As seen earlier, filtering can be a difficult task when working with a limited amount of information. Only with the advance of time one can be increasingly more accurate about the cyclical position at a given period. Nevertheless, the quasi-real first estimate of the composite indicators presents a high correlation with the final one (more than 0.9 for the coincident and almost 0.8 for the leading indicators), the noise-to-signal ratio is relatively low for the coincident indicator and the standard deviation of the corresponding revisions is lower than 0.3 per cent for the coincident indicator and only slightly higher for the leading indicators.

³¹Henceforth, we will refer to the n^{th} estimate for a given t as quasi-real or as quasi-final, depending on the source of uncertainty. However, one should note that only the first estimate corresponds strictly to the definition of quasi-real or quasi-final estimate.

³²Obviously, this requires losing observations at the end of the sample. Nevertheless, it was possible to retain these monthly estimates for a common period of seven years (since we stopped at the 24th estimate).

5 Comparison with other composite indicators

In this section, we proceed into the comparison of the proposed frequency band composite indicators with other alternative approaches. A possible alternative approach would be to choose the variables to be included in the composite indicators according to their overall comovement properties, i.e., disregarding the frequency band differences. Following a similar criteria to the one used in the previous section, the non-frequency band approach led us to the selection of the variables presented in Table 3 for each composite indicator (with the respective weights). Interestingly, the variables chosen with the non-frequency band approach ended up being a subset of the variables selected with the frequency band approach. This can be explained by the fact that it is hard to find a variable that presents the desired properties in terms of comovement and time displacement for the business cycle frequency range as whole without revealing those characteristics at any frequency band while the opposite is not true. Therefore, the frequency band approach becomes increasingly more important when the desired time lead increases since, as it is clear from Tables 1 and 2, it is harder to find overall good leading indicators (in terms of both time lead and comovement) than coincident ones.

In Figures 8 and 9, we plot the resulting composite indicators against the reference business cycle and the corresponding comovement statistics are presented in Table 4. One can conclude that the frequency band approach provides better results than its counterpart and, as expected, the improvement becomes more significant with the increase of the desired time lead.

Regarding other composite indicators proposed in the literature, we focus on €COIN and CLI, which are being regularly released by CEPR and OECD, respectively. The €COIN, developed by Altissimo *et al.* (2001), is intended to be a coincident indicator for the euro area GDP quarterly growth and is based on a large dataset (almost a thousand series). The model underlying €COIN can be described briefly in the following way. Each series in the dataset is modelled as the sum of two uncorrelated components, the common and the idiosyncratic. The common component is driven by a small number of shocks which affect all the variables, while the idiosyncratic component is specific to each variable. The €COIN is the common component of the GDP growth rate after discarding its high frequency component. On

the other hand, the well known CLI is intended to lead economic developments in the euro area and is calculated as the weighted average of the CLIs for the countries belonging to the euro area (see OECD (1987)). Although the reference series used by the OECD is the industrial production index, OECD states that CLI can be used to lead the GDP cyclical component. In Figures 8 and 9, we plot the cyclical component of €COIN³³ and CLI, respectively. According to Table 4, one can conclude that €COIN and CLI present similar overall results to those obtained with the frequency band coincident and short-leading indicators, respectively.

Until now, we have been focusing on GDP deviations from trend, i.e., the above composite indicators can be used as a proxy for the output gap. But, the policy maker can also be interested in tracking GDP quarterly growth evolution. However, the erratic behaviour of the GDP quarterly growth rate difficults its analysis. Hence, as a by-product, one can assess how the previously developed composite indicators perform in tracking the GDP quarterly growth. To make this assessment feasible we trend restored the composite indicators obtained using both the frequency and non-frequency band approaches with GDP trend. Excluding €COIN, we then computed the corresponding quarter-on-quarter growth rate. From Figures 10 and 11 analysis³⁴, one can conclude that all the composite indicators provide a smoother picture of the economic activity developments than the GDP quarterly growth rate. Regarding the coincident indicators, although all the indicators present a similar overall behaviour, the coincident indicator seems to be less affected by erratic movements than €COIN, which allows it to provide an even more clear signal regarding the current GDP quarterly growth evolution. Concerning the leading indicators, the CLI has a lead of around one quarter while the short and long-leading indicators provide signals with an advance of two and three quarters, respectively (see Table 4).

³³Since €COIN tracks the GDP quarterly growth rate we computed the corresponding index and then isolated the cyclical component with the band-pass filter.

³⁴Regarding CLI, for presentation purposes, we normalize the resulting quarterly growth rate series such that it has the same mean and standard deviation of GDP quarterly growth rate.

6 Conclusions

The main purpose of this paper was to construct monthly coincident and leading composite indicators for the euro area business cycle. Once defined the euro area reference business cycle, we assessed the lead/lag properties of several economic indicators. However, instead of focusing at the overall comovement between the variables as it is common in the literature, we have shown how one can resort to both time and frequency domain analysis to attain further insight about their relationship. We found that, in general, the characteristics of the indicators vary across frequency bands. In order to take advantage of this in the construction of the coincident and leading composite indicators, we selected and used the indicators only wherever they exhibit the desired properties in terms of comovement and time displacement. Regarding the leading indicators, we considered both short and long-leading composite indicators (with a time lead of around 2 and 4 quarters, respectively). The resulting composite indicators present a noteworthy performance and are not outperformed by other alternative approaches. In particular, it was found that the proposed frequency band approach becomes more important when the focus lies on leading indicators.

Appendix

The available data regarding the euro area as a whole is rather limited. This is even a more serious problem when the focus is on monthly series³⁵. As far as possible, we used the series provided by the euro area official statistical sources, i.e., the Eurostat, the European Commission and the ECB, to ensure that the data used in this paper is the same one used on euro area economic monitoring. However, in some cases, due to the shorter time span availability, we had to chain the official time series with an euro area aggregate proxy, constructed by us or made available by other institutions (e.g. OECD (Main Economic Indicators)). Following Fagan *et al.* (2001), our euro area aggregates were obtained weighting country level data with 1995 (PPP) GDP weights, which were rescaled whenever there was any missing data for a country. It was possible to collect more than 50 monthly

³⁵For example, Altissimo *et al.* (2001) who gathered a panel of 951 monthly time series, starting from January 1987, for the euro area, were only able to include 14 series regarding the euro area as a whole.

indicators covering several aspects of the euro area economy from January 1987 to December 2001.

Regarding real GDP, the seasonally adjusted series provided by the Eurostat only starts in the first quarter of 1991. Therefore, from 1991 backwards we used the series provided by Fagan *et al.* (2001) to obtain a quarterly series for the above mentioned sample period.

All series related to surveys are seasonally adjusted and provided by the European Commission.

The industrial production volume indices are seasonally adjusted and provided by the Eurostat. However, for capital, consumer and intermediate goods, the euro area series only start in January 1995 while for the manufacturing sector it begins in January 1990. Therefore, we resorted to country level data provided by the Eurostat to fulfil the time span requirement.

The unemployment series is also seasonally adjusted and provided by the Eurostat. Since there is no official series before June 1991, an aggregate series was obtained, in this particular case, by summing country level data.

Regarding new passenger car registrations, the seasonally adjusted series is provided by the ECB since January 1990. From 1990 backwards, we used the OECD euro area series.

The retail sales volume index is seasonally adjusted and provided by the Eurostat since 1996. To obtain a longer time span series, we resorted to country level data provided by the OECD.

Nominal monetary aggregates are seasonally adjusted and released by the ECB. They were deflated with the euro area Harmonized Index of Consumer Prices (HICP), which before 1990 was calculated using CPI country level data.

Regarding nominal interest rates, since both short and long-term interest rates are made available by the ECB only for the period after January 1994, we had also to use OECD country level data. Nominal short-term interest rate refers to the 3-month deposits money market rate and the nominal long-term interest rate refers to the 10-year government bond yield. The yield curve spread is given by the difference between the long and the short-term interest rate. The real short-term interest rate was obtained by subtracting the inflation rate from the nominal short-term interest rate.

The real effective exchange rate of the euro refers to the ECB series (with the broadest coverage in terms of trading partners). However, since it was

not available before January 1993, we also used the series provided by the OECD.

Concerning stock prices, the series considered were Dow Jones Euro Stoxx price indices for several economic sectors.

Excluding surveys and interest rates, all data are in logarithms.

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Table 1: Frequency domain analysis of comovements with the euro area business cycle

	Standard business cycles (6 to 32 quarters)			Long cycles (20 to 32 quarters)			Medium cycles (12 to 20 quarters)			Short cycles (6 to 12 quarters)		
	Cross-correlation			Cross-correlation			Cross-correlation			Cross-correlation		
	at lag 0	maximum	at lag ^(a)	at lag 0	maximum	at lag	at lag 0	maximum	at lag	at lag 0	maximum	at lag
Surveys												
Industrial confidence indicator ^(b)	0.69	0.76	-0.9	0.44	0.97	-3.8	0.69	0.77	-1.1	0.89	0.91	-0.3
Production trend observed in recent months	0.68	0.73	-0.7	0.22	0.95	-4.7	0.69	0.72	-0.7	0.93	0.94	-0.3
Assessment of order books	0.69	0.74	-0.8	0.52	0.97	-3.5	0.80	0.84	-0.7	0.85	0.86	0.2
Assessment of export order books	0.55	0.62	-1.0	0.29	0.96	-4.4	0.68	0.73	-0.9	0.87	0.87	0.1
Assessment of stocks of finished products	-0.65	-0.67	-0.5	-0.32	-0.98	-4.4	-0.77	-0.79	-0.5	-0.79	-0.79	0.0
Production expectations	0.58	0.71	-1.3	0.22	0.86	-4.5	0.71	0.82	-1.4	0.82	0.89	-0.6
Selling-price expectations	0.64	0.65	-0.4	0.17	0.57	-4.6	0.69	0.74	-0.8	0.64	0.81	1.1
Construction confidence indicator ^(c)	0.77	0.82	-0.9	0.73	0.78	-1.3	0.81	0.93	-1.5	0.72	0.73	0.3
Trend of activity compared with preceding months	0.67	0.76	-1.2	0.26	0.89	-4.4	0.77	0.95	-1.7	0.73	0.80	0.6
Assessment of order books	0.77	0.78	-0.4	0.91	0.95	-1.0	0.81	0.88	-1.1	0.67	0.72	0.6
Employment expectations	0.74	0.85	-1.3	0.32	0.58	-3.4	0.78	0.96	-1.8	0.76	0.76	0.0
Price expectations	0.82	0.88	-0.9	0.80	0.84	-1.1	0.85	0.93	-1.0	0.76	0.76	0.1
Retail trade confidence indicator ^(d)	0.81	0.83	-0.4	0.97	0.97	0.4	0.80	0.86	-1.0	0.72	0.72	0.0
Present business situation	0.89	0.89	0.2	0.97	0.97	0.2	0.88	0.88	0.1	0.87	0.88	0.2
Assessment of stocks	0.14	-0.30	-5.6	-0.86	-0.87	0.3	0.49	-0.60	-6.5	0.13	0.15	-0.6
Intentions of placing orders	0.69	0.76	-0.7	0.72	0.77	1.4	0.81	0.81	0.1	0.68	0.77	-0.8
Expected business situation	0.81	0.85	-0.8	0.99	0.99	-0.1	0.90	0.95	-0.8	0.37	0.52	-1.1
Employment expectations	0.66	0.77	-1.2	0.95	0.99	-1.0	0.91	0.97	-1.0	0.29	0.50	-1.4
Consumer confidence indicator ^(e)	0.70	0.77	-1.0	0.33	0.84	-4.0	0.74	0.95	-1.9	0.86	0.90	0.5
Financial situation of households over last 12 months	0.70	0.75	-0.9	0.96	0.97	-0.5	0.68	0.94	-2.1	0.67	0.90	1.1
Financial situation of households over next 12 months	0.68	0.76	-1.1	0.72	0.88	-2.2	0.63	0.89	-2.2	0.90	0.91	0.2
General economic situation over last 12 months	0.73	0.78	-0.9	0.56	0.86	-3.1	0.76	0.95	-1.8	0.73	0.90	0.9
General economic situation over next 12 months	0.61	0.75	-1.5	0.01	0.80	-5.4	0.69	0.95	-2.1	0.90	0.91	0.2
Price trends over last 12 months	0.46	0.69	1.8	0.54	0.79	3.2	0.54	0.90	2.0	0.36	-0.59	-4.3
Price trends over next 12 months	0.34	0.80	2.6	0.70	0.99	2.9	0.68	0.96	2.1	-0.19	-0.55	-1.7
Unemployment over next 12 months	-0.64	-0.69	-0.9	-0.42	-0.96	-3.9	-0.88	-0.90	-0.5	-0.72	-0.77	0.6
Major purchases at present	0.28	0.40	-1.7	-0.43	-0.59	2.7	0.31	0.48	-1.9	0.88	0.88	0.0
Major purchases over next 12 months	0.79	0.80	0.5	0.97	0.98	-0.5	0.83	0.83	-0.4	0.58	0.77	1.1
Savings at present	0.70	0.74	-0.8	0.87	0.87	-0.1	0.80	0.83	-0.7	0.19	0.36	-1.7
Savings over next 12 months	0.77	0.78	-0.4	0.97	0.98	0.5	0.68	0.85	-1.7	0.89	0.96	0.5
Retail sales and car registrations												
Retail sales (volume)	0.80	0.83	0.8	0.89	0.93	1.1	0.94	0.96	0.6	-0.03	0.27	-4.7
New passenger car registrations	0.69	0.69	0.2	0.60	0.92	2.9	0.76	0.78	-0.7	0.61	0.68	0.6
Industrial production												
IPI (Industry excluding construction) (volume)	0.95	0.95	0.1	1.00	1.00	0.1	0.95	0.96	-0.4	0.94	0.95	0.3
IPI (Manufacturing) (volume)	0.94	0.94	0.1	1.00	1.00	-0.2	0.90	0.92	-0.5	0.96	0.96	0.2
IPI (Capital goods) (volume)	0.93	0.94	0.3	0.97	0.99	-0.7	0.89	0.98	1.0	0.94	0.95	0.2
IPI (Consumer goods) (volume)	0.85	0.85	-0.1	0.75	0.85	1.8	0.90	0.92	-0.5	0.73	0.75	0.4
IPI (Intermediate goods) (volume)	0.84	0.87	-0.6	0.98	0.99	-0.6	0.86	0.96	-1.0	0.91	0.92	0.2
Labour market												
Unemployment	-0.68	-0.87	1.4	-0.93	-0.99	1.2	-0.74	-0.90	1.3	-0.61	-0.92	1.4
Money, interest rates and exchange rate^(f)												
M1 (nominal)	0.16	0.81	-3.4	0.55	0.55	-0.2	0.11	0.98	-4.0	0.11	0.72	-2.3
M1 (real)	0.16	0.77	-3.4	0.39	0.40	-0.4	0.14	0.96	-4.1	0.09	0.69	-2.4
M3 (nominal)	-0.60	-0.63 (0.51)	0.7 (-9.1)	0.32	0.47	-3.6	-0.97	-0.97 (0.93)	0.0 (-8.1)	-0.14	0.48	-3.0
M3 (real)	-0.61	-0.67 (0.52)	1.1 (-7.4)	-0.18	0.74	-6.4	-0.92	-0.93 (0.92)	0.4 (-7.8)	-0.16	0.44	-3.4
Long-term interest rate (nominal)	0.75	0.78	0.6	0.86	0.86	-0.1	0.86	0.86	0.3	0.34	0.54 (-0.38)	1.4 (-3.4)
Short-term interest rate (nominal)	0.32	-0.55	-3.8	0.62	0.9 (-0.81)	3.1 (-8.7)	0.37	-0.92	-4.8	0.12	0.78 (-0.56)	1.9 (-2.0)
Short-term interest rate (real)	0.25	-0.59	-3.6	0.12	-0.48	-6.3	0.07	-0.82	-4.3	0.45	0.82 (-0.56)	1.5 (-3.1)
Interest rate spread	0.39	0.66	-2.3	0.73	0.74	0.6	0.41	0.92	-2.8	0.04	0.15	-1.4
Real effective exchange rate	0.19	-0.28	-3.2	0.77	0.81 (-0.77)	1.1 (-9.7)	0.13	-0.22	-4.5	0.20	-0.78	-2.7
Stock market indices												
Dow Jones Euro Stoxx	0.39	0.81	-2.6	-0.24	-0.46	-3.8	0.44	0.94	-2.8	0.33	0.52	-1.1
Dow Jones Euro Stoxx - Basic Materials	0.16	0.52	-2.3	0.29	0.92	-4.7	-0.14	0.63	-4.7	0.36	0.68	-1.4
Dow Jones Euro Stoxx - Consumer Cyclical	0.28	0.79	-2.8	-0.18	-0.37	-4.1	0.28	0.94	-3.1	0.51	0.71	-1.0
Dow Jones Euro Stoxx - Automobiles	0.09	0.56	-2.9	-0.64	-0.66	-0.9	0.12	0.84	-3.4	0.37	0.50	-0.9
Dow Jones Euro Stoxx - Cyclical Goods & Services	0.39	0.81	-2.2	0.43	0.80	4.0	0.38	0.95	-2.6	0.50	0.73	-1.1
Dow Jones Euro Stoxx - Retail	0.20	0.86	-3.2	0.14	-0.53	-7.3	0.21	0.96	-3.4	0.07	0.39	-1.6
Dow Jones Euro Stoxx - Industrial	0.54	0.83	-2.1	-0.05	-0.23	-5.2	0.59	0.94	-2.4	0.45	0.69	-1.1
Dow Jones Euro Stoxx - Construction	0.18	0.73	-2.9	-0.02	0.23	-5.9	0.20	0.89	-3.6	0.20	0.67	-1.6
Dow Jones Euro Stoxx - Industrial Goods & Services	0.55	0.75	-1.5	0.15	-0.32	-7.3	0.57	0.80	-1.6	0.69	0.85	-1.1

Notes:

(a) A positive lag indicates that the indicator is lagging the reference series, while a negative lag implies that it is leading.

(b) The industrial confidence indicator is the average of the questions on production expectations, order-books and stocks (with inverted sign).

(c) The construction confidence indicator is the average of the questions on order-books and employment expectations.

(d) The retail trade confidence indicator is the average of the questions on the present and the future business situation, and stocks (with inverted sign).

(e) The consumer confidence indicator is the average of the questions on the financial situation of households, the general economic situation, unemployment expectations (with inverted sign) and savings, all over the next 12 months.

(f) In parenthesis appear the statistics for another local absolute cross-correlation maximum.

Table 2: Time domain analysis of comovements with the euro area business cycle

	Standard business cycles (6 to 32 quarters)			Long cycles (20 to 32 quarters)			Medium cycles (12 to 20 quarters)			Short cycles (6 to 12 quarters)		
	Cross-correlation			Cross-correlation			Cross-correlation			Cross-correlation		
	at lag 0	maximum	at lag ^(a)	at lag 0	maximum	at lag	at lag 0	maximum	at lag	at lag 0	maximum	at lag
Surveys												
Industrial confidence indicator ^(b)	0.71	0.73	-1	0.50	0.76	-3	0.59	0.76	-2	0.82	0.82	0
Production trend observed in recent months	0.63	0.66	-1	0.29	0.70	-4	0.51	0.73	-2	0.90	0.90	0
Assessment of order books	0.74	0.74	0	0.59	0.79	-3	0.63	0.74	-1	0.82	0.82	0
Assessment of export order books	0.63	0.63	0	0.44	0.74	-3	0.32	0.46	-2	0.85	0.85	0
Assessment of stocks of finished products	-0.61	-0.66	-1	-0.27	-0.70	-4	-0.60	-0.77	-2	-0.73	-0.73	0
Production expectations	0.67	0.75	-1	0.44	0.72	-3	0.50	0.76	-2	0.80	0.85	-1
Selling-price expectations	0.59	0.59	0	0.17	0.59	-4	0.90	0.90	0	0.65	0.65	0
Construction confidence indicator^(c)												
Construction confidence indicator ^(c)	0.76	0.79	-1	0.81	0.85	-1	0.66	0.85	-2	0.77	0.77	0
Trend of activity compared with preceding months	0.66	0.70	-1	0.49	0.74	-3	0.63	0.82	-2	0.68	0.68	0
Assessment of order books	0.78	0.78	0	0.90	0.92	-1	0.67	0.84	-2	0.69	0.69	0
Employment expectations	0.72	0.78	-1	0.66	0.76	-2	0.66	0.86	-2	0.78	0.78	0
Price expectations	0.76	0.80	-1	0.80	0.83	-1	0.52	0.81	-2	0.77	0.77	0
Retail trade confidence indicator^(d)												
Retail trade confidence indicator ^(d)	0.80	0.80	0	0.96	0.97	1	0.55	0.89	-2	0.60	0.60	0
Present business situation	0.77	0.77	0	0.94	0.96	1	0.32	0.90	-3	0.80	0.80	0
Assessment of stocks	-0.27	-0.32	-2	-0.69	-0.87	-3	0.06	-0.83	-4	0.24	0.27	-1
Intentions of placing orders	0.62	0.62	0	0.86	0.90	1	0.40	0.52	-2	0.38	0.44	-1
Expected business situation	0.76	0.76	-1	0.98	0.98	0	0.84	0.92	-1	0.31	0.41	-1
Employment expectations	0.68	0.68	0	0.98	0.98	0	0.73	0.89	-2	0.13	0.13	0
Consumer confidence indicator^(e)												
Consumer confidence indicator ^(e)	0.70	0.71	-1	0.49	0.71	-3	0.58	0.76	-2	0.83	0.83	0
Financial situation of households over last 12 months	0.76	0.76	0	0.95	0.96	-1	0.63	0.76	-2	0.63	0.76	1
Financial situation of households over next 12 months	0.74	0.76	-1	0.74	0.85	-2	0.56	0.75	-2	0.87	0.87	0
General economic situation over last 12 months	0.74	0.74	0	0.78	0.85	-2	0.58	0.78	-2	0.75	0.77	1
General economic situation over next 12 months	0.60	0.67	-1	0.26	0.64	-4	0.47	0.76	-2	0.83	0.83	0
Price trends over last 12 months	0.45	0.53	1	0.51	0.52	-1	0.19	-0.63	-4	0.50	-0.60	-5
Price trends over next 12 months	0.36	0.70	3	0.77	0.86	2	0.76	0.86	1	-0.17	-0.46	-2
Unemployment over next 12 months	-0.67	-0.67	0	-0.41	-0.66	-3	-0.67	-0.76	-1	-0.76	-0.76	0
Major purchases at present	0.22	0.28	-1	-0.23	-0.27	2	0.29	0.51	-3	0.81	0.81	0
Major purchases over next 12 months	0.73	0.73	0	0.95	0.95	0	0.62	0.62	0	0.63	0.68	1
Savings at present	0.64	0.65	-1	0.79	0.79	0	0.47	0.70	-2	0.37	0.50	-1
Savings over next 12 months	0.79	0.79	0	0.94	0.94	1	0.60	0.72	-2	0.82	0.82	0
Retail sales and car registrations												
Retail sales (volume)	0.62	0.65	1	0.86	0.90	1	0.97	0.97	0	-0.04	0.38	-5
New passenger car registrations	0.53	0.56	1	0.44	0.81	4	0.89	0.89	0	0.59	0.59	0
Industrial production												
IPI (Industry excluding construction) (volume)	0.94	0.94	0	0.99	0.99	0	0.91	0.93	-1	0.88	0.88	0
IPI (Manufacturing) (volume)	0.93	0.93	0	0.99	0.99	0	0.89	0.91	-1	0.87	0.87	0
IPI (Capital goods) (volume)	0.93	0.93	0	0.94	0.94	0	0.96	0.96	0	0.90	0.90	0
IPI (Consumer goods) (volume)	0.81	0.81	0	0.75	0.87	2	0.82	0.93	-1	0.82	0.84	1
IPI (Intermediate goods) (volume)	0.84	0.84	0	0.93	0.93	0	0.67	0.80	-1	0.86	0.86	0
Labour market												
Unemployment	-0.76	-0.87	1	-0.89	-0.95	1	-0.86	-0.86	0	-0.45	-0.83	2
Money, interest rates and exchange rate^(f)												
M1 (nominal)	0.09	0.55	-3	-0.17	-0.38 (0.13)	3 (-7)	0.07	0.83	-4	0.08	0.51	-2
M1 (real)	0.01	0.51	-4	-0.32	-0.53 (0.25)	3 (-8)	0.11	0.81	-4	0.05	0.45	-3
M3 (nominal)	-0.42	-0.44 (0.30)	1 (-7)	-0.06	-0.47	-5	-0.86	-0.86 (0.85)	0 (-7)	-0.15	-0.28 (0.19)	3 (-7)
M3 (real)	-0.50	-0.55 (0.43)	1 (-7)	-0.49	-0.50	-1	-0.75	-0.75 (0.79)	0 (-7)	-0.19	0.29	-6
Long-term interest rate (nominal)	0.74	0.76	1	0.79	0.79	0	0.84	0.84	0	0.58	0.68 (-0.51)	1 (-4)
Short-term interest rate (nominal)	0.43	0.77 (-0.52)	2 (-4)	0.61	0.95 (-0.78)	3 (-8)	-0.06	-0.68	-3	0.57	0.77 (-0.60)	1 (-4)
Short-term interest rate (real)	0.22	0.65 (-0.63)	2 (-4)	0.07	-0.71	-6	-0.02	-0.69	-3	0.53	0.83 (-0.63)	1 (-4)
Interest rate spread	0.33	0.61	-2	0.31	0.66	-4	0.75	0.92	-2	-0.10	-0.33 (0.25)	2 (-3)
Real effective exchange rate	0.16	-0.33	-3	0.26	-0.61	-7	0.52	0.52 (-0.42)	0 (-9)	0.15	-0.75	-3
Stock market indices												
Dow Jones Euro Stoxx	0.09	0.26	-2	-0.29	-0.32	-2	-0.39	0.84	-5	0.53	0.68	-1
Dow Jones Euro Stoxx - Basic Materials	0.14	0.47	-2	0.55	0.80	-3	-0.63	0.82	-6	0.49	0.82	-1
Dow Jones Euro Stoxx - Consumer Cyclical	0.16	0.32	-2	-0.17	-0.32	-4	-0.34	0.90	-5	0.60	0.77	-1
Dow Jones Euro Stoxx - Automobiles	0.02	0.25	-2	-0.28	-0.35	-2	-0.41	0.87	-5	0.53	0.73	-1
Dow Jones Euro Stoxx - Cyclical Goods & Services	0.35	0.40	-1	0.29	-0.63	-8	-0.23	0.83	-5	0.50	0.65	-1
Dow Jones Euro Stoxx - Retail	0.14	0.36	-2	0.10	-0.43	-7	-0.21	0.89	-5	0.37	0.65	-1
Dow Jones Euro Stoxx - Industrial	0.28	0.48	-2	0.05	0.12	-3	-0.26	0.82	-5	0.63	0.82	-1
Dow Jones Euro Stoxx - Construction	0.23	0.55	-2	0.59	0.59	0	-0.34	0.92	-5	0.43	0.76	-1
Dow Jones Euro Stoxx - Industrial Goods & Services	0.29	0.40	-2	-0.07	0.06	-5	-0.18	0.63	-5	0.69	0.78	-1

Notes:

(a) A positive lag indicates that the indicator is lagging the reference series, while a negative lag implies that it is leading.

(b) The industrial confidence indicator is the average of the questions on production expectations, order-books and stocks (with inverted sign).

(c) The construction confidence indicator is the average of the questions on order-books and employment expectations.

(d) The retail trade confidence indicator is the average of the questions on the present and the future business situation, and stocks (with inverted sign).

(e) The consumer confidence indicator is the average of the questions on the financial situation of households, the general economic situation, unemployment expectations (with inverted sign) and savings, all over the next 12 months.

(f) In parenthesis appear the statistics for another local absolute cross-correlation maximum.

Table 3: Composite indicators' weights

	Long cycles	Medium cycles	Short cycles	Non-frequency band approach
Coincident composite indicator				
Construction confidence indicator	-	-	0.248	-
Present business situation (Retail trade survey)	0.327	-	0.229	0.332
Consumer confidence indicator	-	-	0.265	-
Financial situation of households over last 12 months (Consumers survey)	0.328	-	-	0.326
Retail sales (volume)	-	0.347	-	-
New passenger car registrations	-	0.332	-	-
IPI (Industry excluding construction) (volume)	0.345	0.321	0.258	0.342
<i>Proportion of variance explained by the first principal component</i>	0.925	0.890	0.847	0.827
Short-leading composite indicator				
Industrial confidence indicator	-	0.187	-	0.214
Construction confidence indicator	0.500	0.207	-	0.228
Expected business situation (Retail trade survey)	-	0.213	-	0.194
Consumer confidence indicator	-	0.207	-	-
Financial situation of households over next 12 months (Consumers survey)	0.500	-	-	0.229
Interest rate spread	-	0.185	-	0.135
Real effective exchange rate (with inverted sign)	-	-	1.000	-
<i>Proportion of variance explained by the first principal component</i>	0.985	0.852	1.000	0.711
Long-leading composite indicator				
Industrial confidence indicator	0.215	-	-	-
Trend of activity compared with preceding months (Construction survey)	0.212	-	-	-
Assessment of stocks (Retail trade survey) (with inverted sign)	-	0.211	-	-
General economic situation over next 12 months (Consumers survey)	0.213	-	-	-
M1 (real)	-	0.199	-	0.500
Short-term interest rate (real) (with inverted sign)	0.175	0.141	1.000	0.500
Dow Jones Euro Stoxx - Basic Materials	0.184	-	-	-
Dow Jones Euro Stoxx - Consumer Cyclical	-	0.220	-	-
Dow Jones Euro Stoxx - Construction	-	0.229	-	-
<i>Proportion of variance explained by the first principal component</i>	0.843	0.727	1.000	0.670

Table 4: Comovement of the composite indicators with the euro area business cycle and GDP quarterly growth rate

	Business cycles												GDP quarterly growth			
	Standard business cycles (6 to 32 quarters)			Long cycles (20 to 32 quarters)			Medium cycles (12 to 20 quarters)			Short cycles (6 to 12 quarters)			Cross-correlation			
	Cross-correlation			Cross-correlation			Cross-correlation			Cross-correlation			Cross-correlation			
	at lag 0	maximum	at lag	at lag 0	maximum	at lag	at lag 0	maximum	at lag	at lag 0	maximum	at lag	at lag 0	maximum	at lag	
Frequency domain analysis of comovements																
Coincident indicator	0.97	0.97	0.1	1.00	1.00	0.0	1.00	1.00	0.0	0.88	0.89	0.2	0.81	0.82	0.2	
Short-Leading indicator	0.54	0.84	-2.0	0.83	0.95	-1.8	0.71	0.91	-1.8	0.05	0.66	-2.3	0.42	0.69	-2.3	
Long-Leading indicator	0.08	0.87	-3.6	0.63	0.97	-3.1	0.01	0.97	-4.2	-0.50	0.68	-3.3	0.17	0.56	-2.8	
Coincident Indicator (non-frequency band approach)	0.95	0.95	0.0	0.99	0.99	-0.4	0.96	0.97	-0.4	0.93	0.96	0.4	0.81	0.81	0.2	
Short-Leading Indicator (non-frequency band approach)	0.80	0.91	-1.2	0.57	0.75	-2.5	0.81	0.99	-1.7	0.91	0.91	0.1	0.76	0.77	-0.4	
Long-Leading Indicator (non-frequency band approach)	-0.11	0.75	-3.6	-0.02	0.96	-6.1	-0.03	0.87	-3.9	-0.22	0.74	-3.0	0.16	0.58	-3.0	
€COIN	0.93	0.95	0.4	0.98	0.99	0.6	0.97	0.98	0.4	0.85	0.88	0.4	0.78	0.78	0.1	
CLI	0.64	0.93	-1.8	0.56	0.95	-3.5	0.62	0.99	-2.2	0.78	0.91	-0.8	0.42	0.62	-1.6	
Time domain analysis of comovements																
Coincident indicator	0.97	0.97	0	1.00	1.00	0	0.98	0.98	0	0.89	0.89	0	0.75	0.75	0	
Short-Leading indicator	0.59	0.84	-2	0.78	0.85	-2	0.72	0.89	-2	-0.15	0.75	-3	0.47	0.62	-2	
Long-Leading indicator	0.10	0.84	-4	0.42	0.75	-4	-0.15	0.93	-4	-0.53	0.63	-4	0.32	0.56	-3	
Coincident Indicator (non-frequency band approach)	0.91	0.91	0	0.90	0.90	0	0.72	0.90	-2	0.90	0.90	0	0.73	0.73	0	
Short-Leading Indicator (non-frequency band approach)	0.80	0.85	-1	0.59	0.73	-2	0.70	0.88	-2	0.81	0.81	0	0.69	0.69	0	
Long-Leading Indicator (non-frequency band approach)	-0.13	0.69	-4	-0.34	0.56	-7	0.09	0.88	-4	-0.39	0.66	-3	0.33	0.55	-3	
€COIN	0.92	0.92	0	0.96	0.97	1	0.96	0.96	0	0.85	0.85	0	0.77	0.77	0	
CLI	0.65	0.83	-2	0.58	0.80	-3	0.53	0.87	-2	0.62	0.88	-1	0.44	0.56	-1	

Figure 1: Gain function of several filters

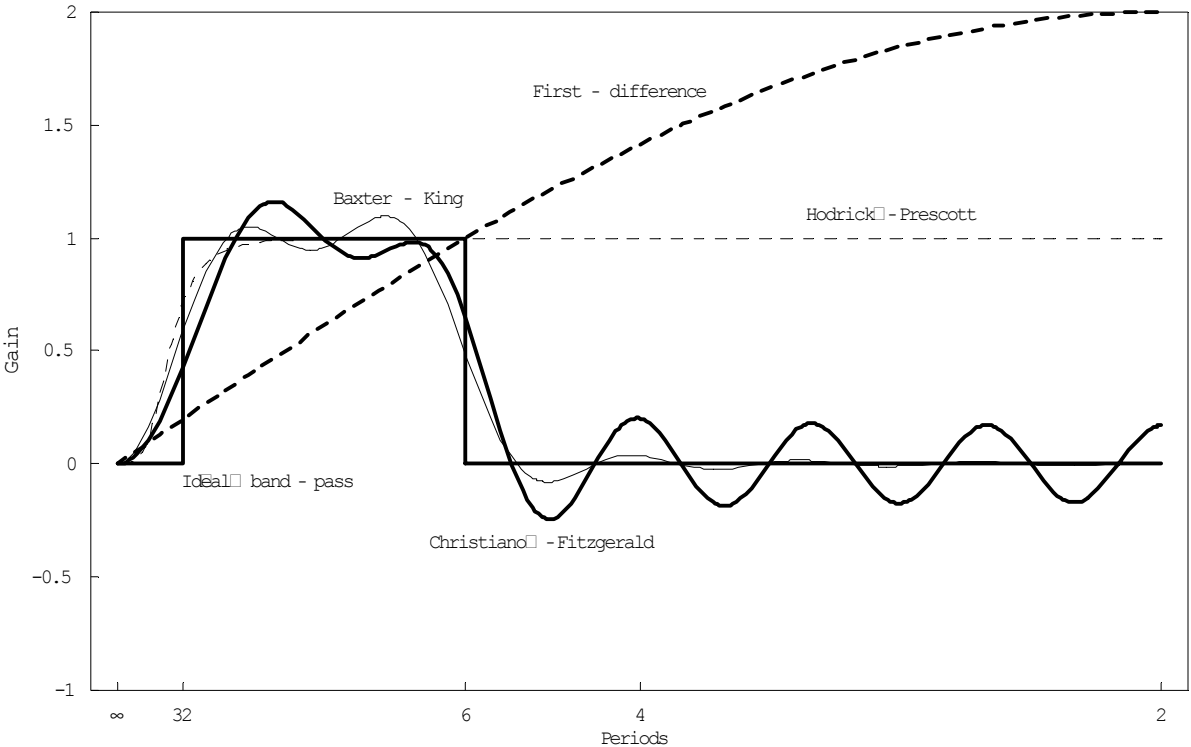


Figure 2: Random walk pseudo -spectrum

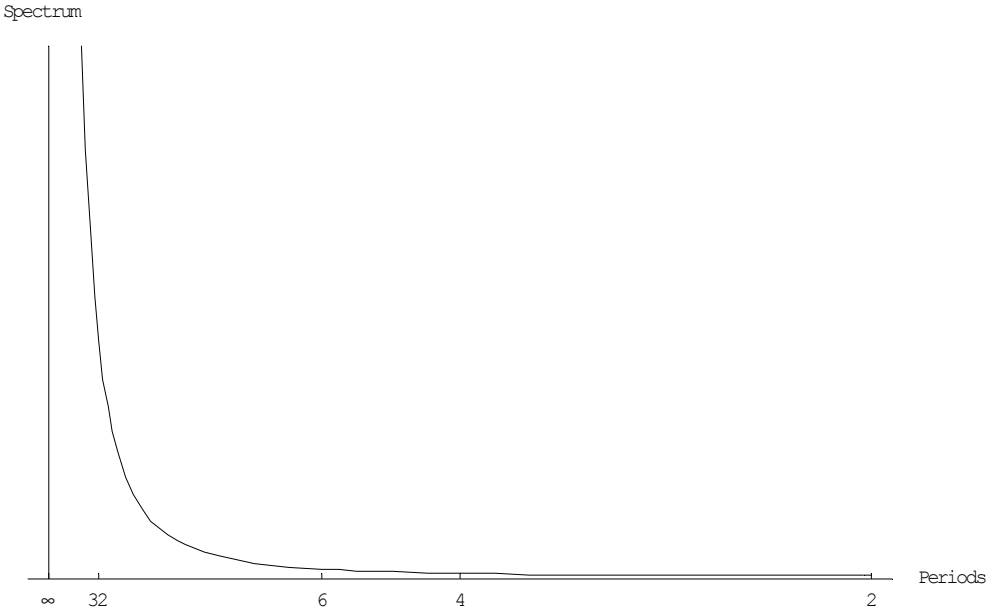


Figure 3: Spectrum of the GDP cyclical component

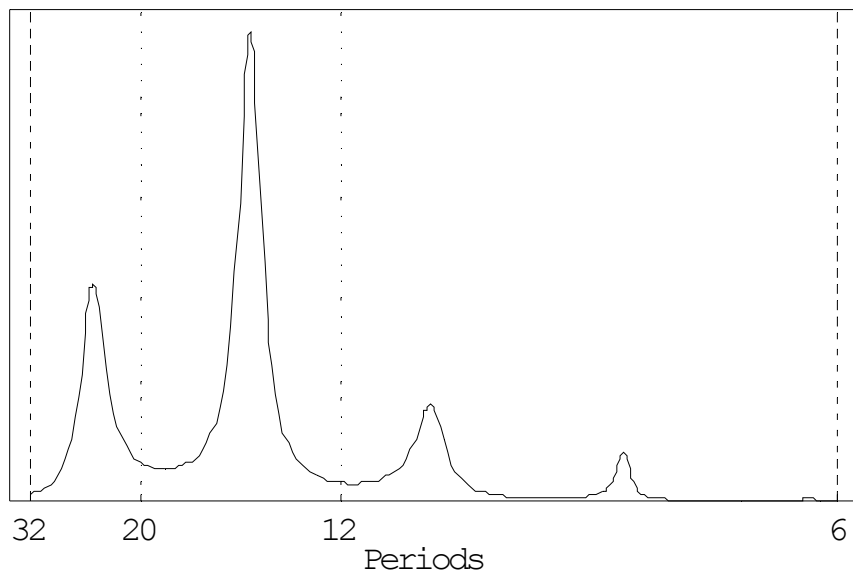


Figure 4: Monthly composite indicators for the euro area business cycle

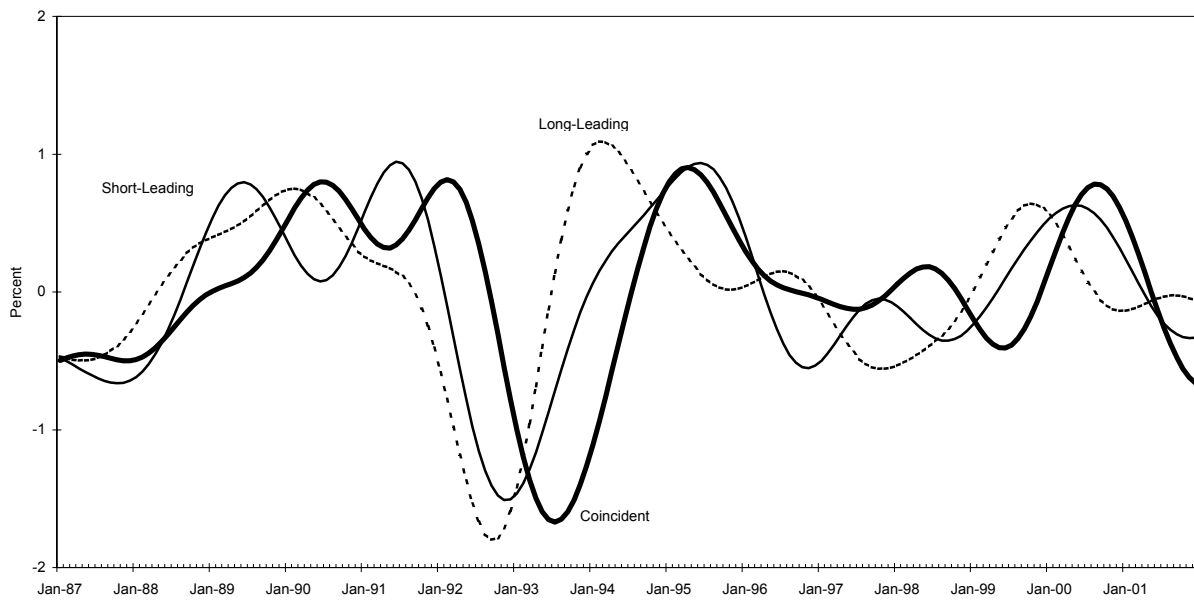


Figure 5: Correlation of the n^{th} estimate with the final estimate of the composite indicator for the euro area business cycle

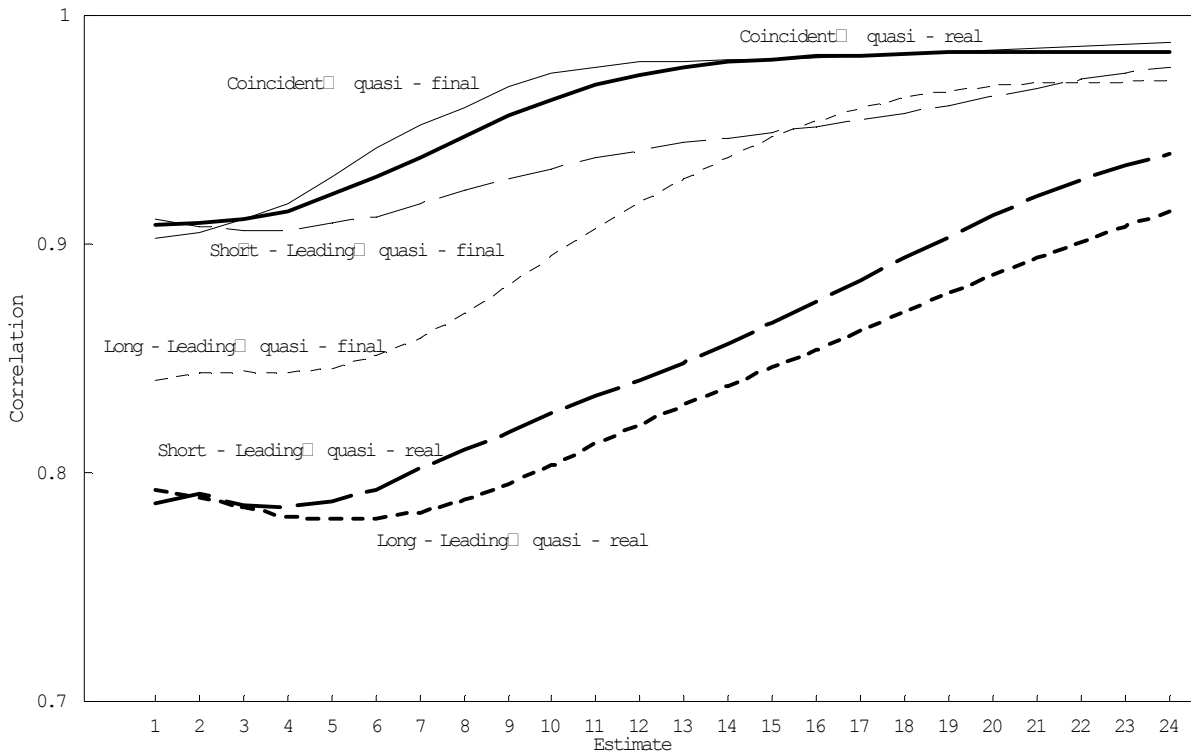


Figure 6: Noise-to-signal ratio of the n^{th} estimate of the composite indicator for the euro area business cycle

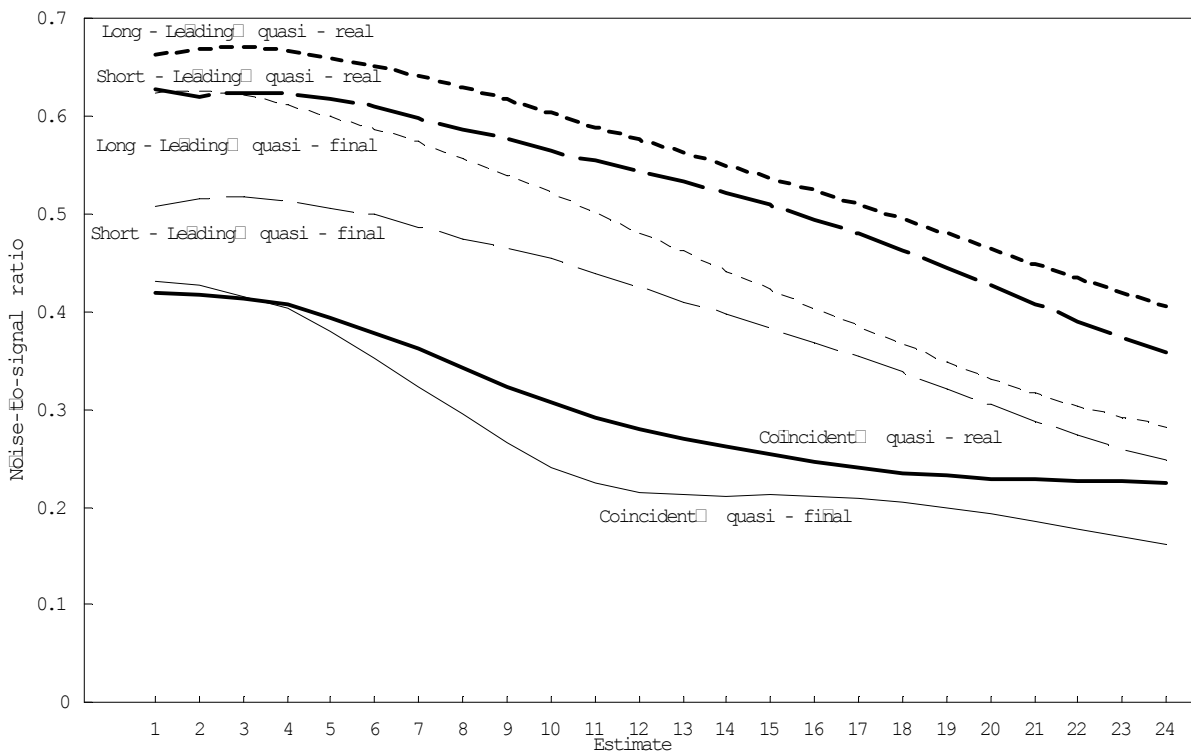


Figure 7: Standard deviation of the revisions of the n^{th} estimate of the composite indicator for the euro area business cycle

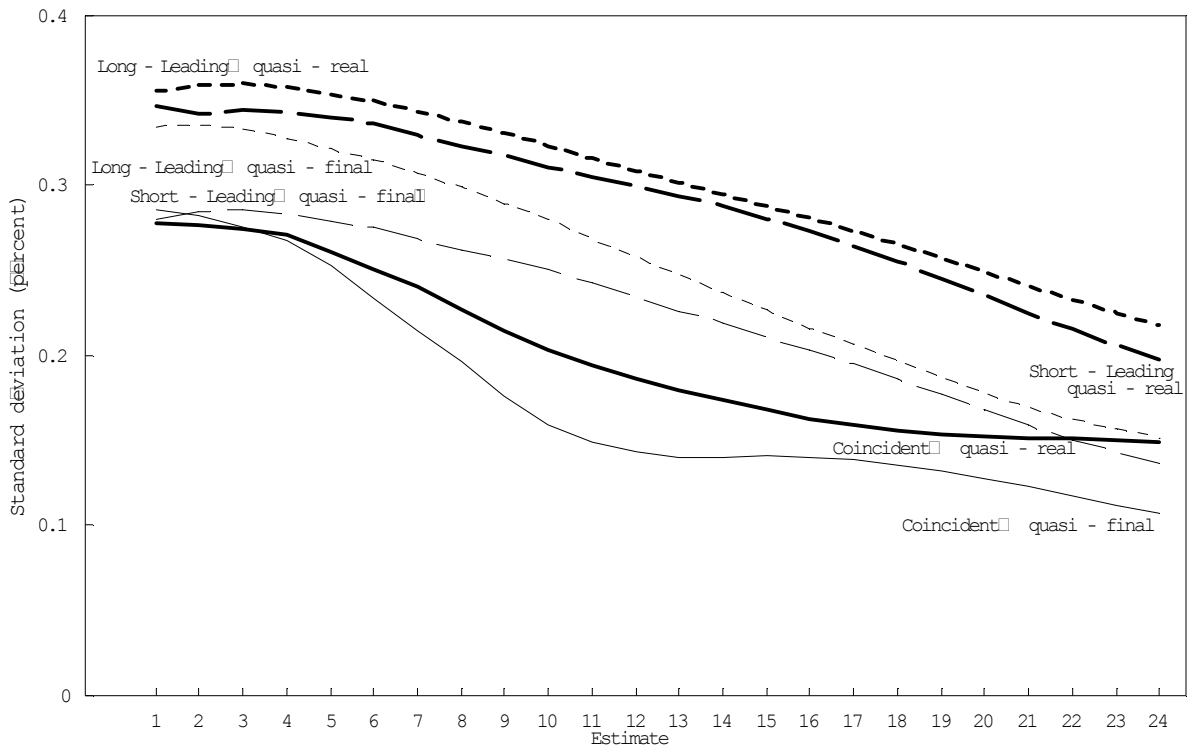


Figure 8: Coincident indicators for the euro area business cycle

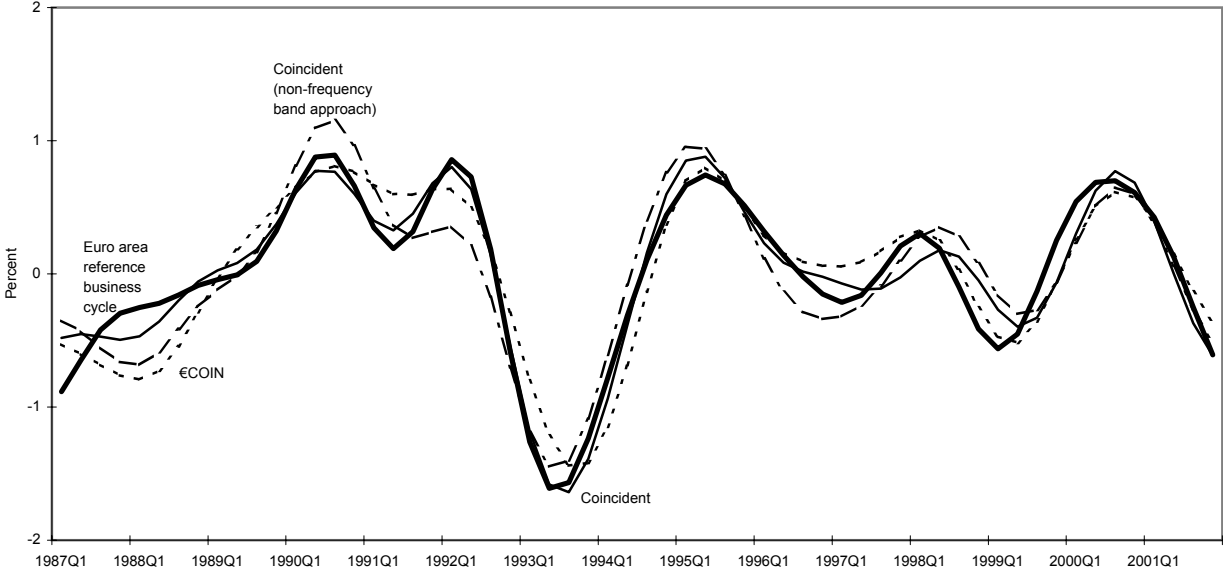


Figure 9: Leading indicators for the euro area business cycle

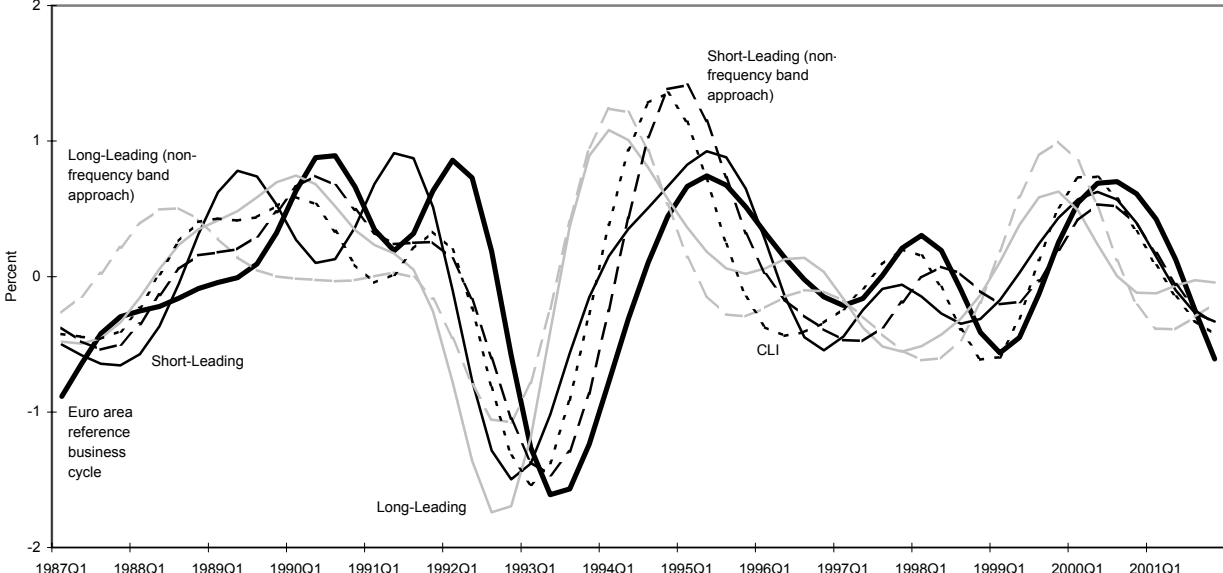


Figure 10: Coincident indicators for the GDP quarterly growth

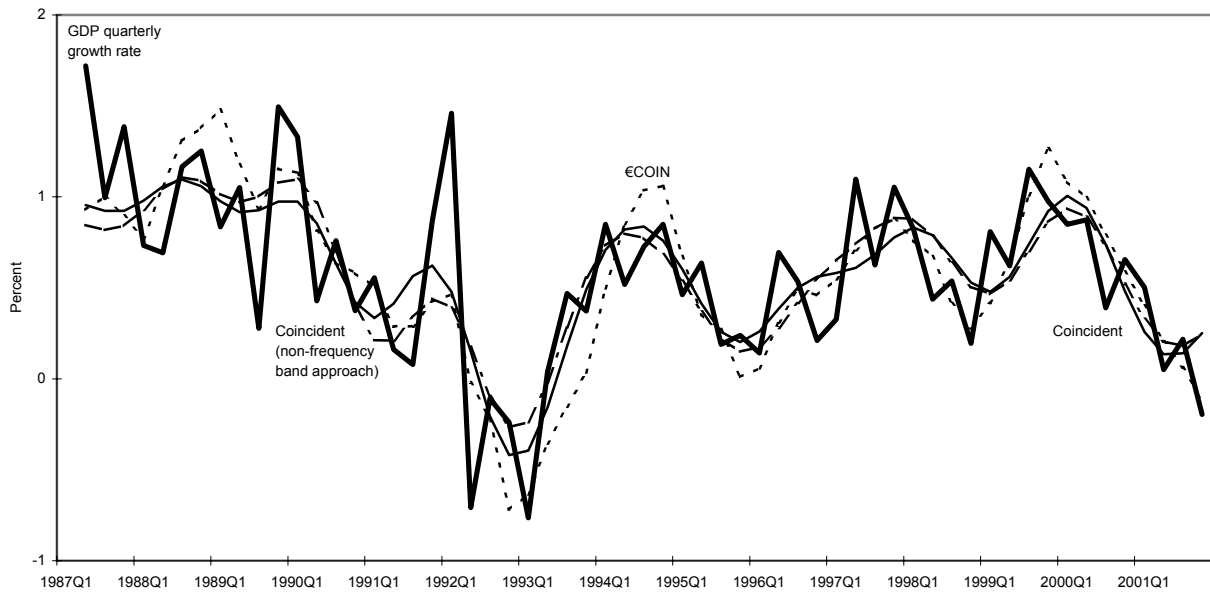
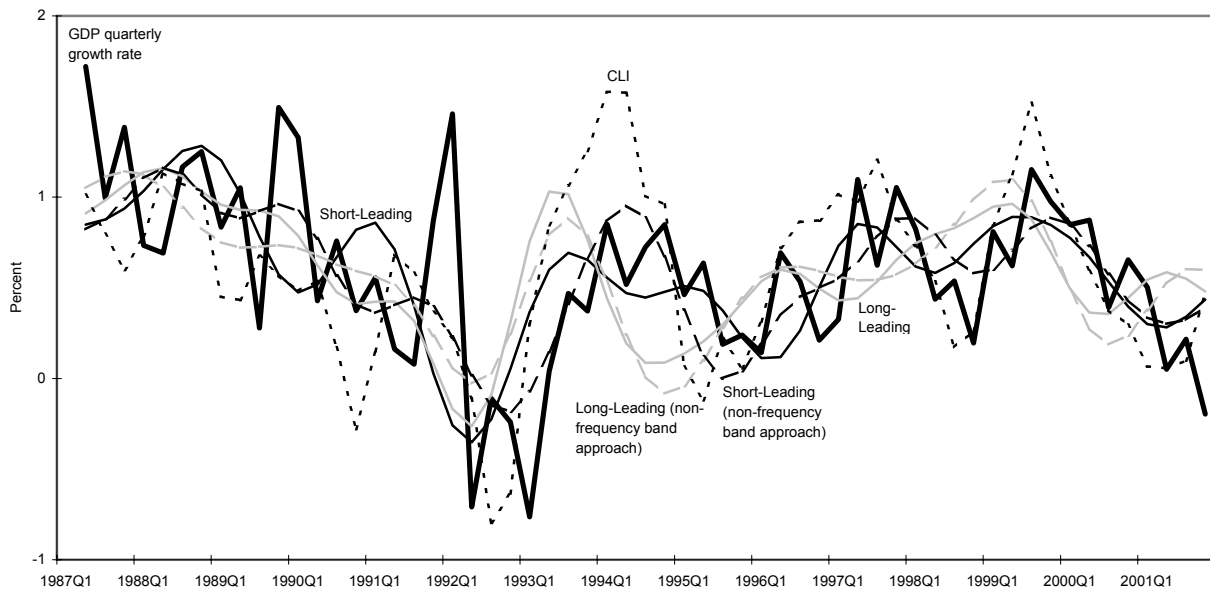


Figure 11: Leading indicators for the GDP quarterly growth



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