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# NEW EUROCOIN: TRACKING ECONOMIC GROWTH IN REAL TIME[*]

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**Abstract**

This paper presents ideas and methods underlying the construction of an indicator that tracks euro-area GDP growth but, unlike GDP growth, (i) is updated monthly and almost in real time, and (ii) is free from short-run dynamics. Removal of short-run dynamics from a time series to isolate the medium to long-run component can be obtained by a band-pass filter. However, it is well known that band-pass filters, being two-sided, perform very poorly at the end of the sample. New Eurocoin is an estimator of the medium to long-run component of GDP that only uses contemporaneous values of a large panel of macroeconomic time series, so that no end-of-sample deterioration occurs. Moreover, as our dataset is monthly, New Eurocoin can be updated each month and with a very short delay. Our method is based on generalized principal components that are designed to use leading variables in the dataset as proxies for future values of GDP growth. As the medium to long-run component of GDP is observable, although with delay, the performance of New Eurocoin at the end of the sample can be measured.

**JEL Classification**: C51; E32; O30.
**Keywords**: coincident indicator, band-pass filter, large-dataset factor models, generalized principal components.

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**Contents**

# 1 Introduction

This paper presents a method to estimate in real time the current state of the economy. The method is applied to the euro area, the geographical focus being motivated by the creation of the European Monetary Union and the implementation of a common monetary policy. The resulting indicator, New Eurocoin (NE henceforth), is intended to replace the Eurocoin indicator proposed by Altissimo et al. (2001) and published monthly by the Centre for Economic Policy Research (see the website www.cepr.org).

The main objective of our indicator is to make an assessment of economic activity that is (a) comprehensive and non-subjective, (b) timely and (c) free from short-run fluctuations. None of the available macroeconomic series provides a measure of the state of the economy that fulfills all such criteria. GDP, the most comprehensive indicator of real activity, fails to meet (b) and (c). Regarding timeliness, GDP is only available quarterly and with a long delay. For instance, the preliminary estimate of euro area GDP for the first quarter of the year becomes available only in May. Moreover, GDP is affected by a sizeable short-run component so that, for example, the beginning of a medium-run upswing cannot be distinguished from a transitory upward movement within a basically negative path.

NE is a real-time estimate of GDP growth, cleaned of short-run oscillations. More precisely,

(i) We focus on the growth rate of GDP and define the *medium to long-run growth*, henceforth denoted by MLRG, as the component of the GDP growth rate obtained by removing the fluctuations of a period shorter than or equal to one year. This medium to long-run component of the GDP growth rate will be our target.
(ii) NE is a monthly and timely estimate of the MLRG for the euro area: by the 25th of each month we are able to produce a reliable estimate for the current month.

Based on the spectral representation of a stationary process, MLRG is defined as including only the oscillations of period longer than one year, and is therefore a "smoothing" of GDP growth. As is well known, such a result can be achieved by applying to GDP growth a band-pass filter that removes high-frequency waves. However, the ideal band-pass filter is an infinite, centred, moving average. The effect of truncation is not uniform over finite samples, with endpoints badly estimated and severely revised as new data become available (see e.g. Baxter and King, 1999; Christiano and Fitzgerald, 2003).

A substantial mitigation of this conflict between timeliness and removal of the short-run fluctuations is the main contribution of the present paper. We obtain a good smoothing by exploiting cross-sectional *current* information from a large dataset. The intuition is that the dataset contains variables that are leading with respect to current GDP. Therefore the information contained in the future of GDP, which is unavailable, can be partially recovered by projecting the MLRG onto a suitable set of linear combinations of current values of these variables.

Constructing such linear combinations is the crucial step of our procedure. We start with a large dataset, containing variables that are closely related to the MLRG. To estimate our unobserved component we could select a small number of them. However, the macroeconomic series used as regressors would necessarily contain a good deal of idiosyncratic (i.e. specific to variable, country, sector, etc.) and short-run noise, which is harmful to the estimation of our indicator. The central idea is that instead of selecting a few macroeconomic variables we can employ a small number of linear combinations of the series in the dataset, in such a way as to remove both variable-specific and short-run sources of fluctuation, while retaining cyclical and long-run movements. To do so we use a particular kind of principal components, which are specifically designed to extract from the dataset the common, medium to long-run information. More precisely, we take the linear combinations of the observable series whose fraction of common, medium to long-run variance is maximal.

Common medium to long-run variance is estimated using the Generalized Dynamic Factor Model (GDFM) proposed by Forni, Hallin, Lippi and Reichlin (2000) and Forni and Lippi (2001). The use of factor models is not new in the literature on coincident indicators, an important reference being Stock and Watson (1989), where the "cycle" is defined as the unique common factor, loaded contemporaneously by a few coincident variables. By contrast, our model is designed to handle a large number of variables affected by more than one common source of variation. Moreover, the factors are loaded with quite general impulse-response functions, so as to represent leading, coincident and lagging series (for models with these features, see also Stock and Watson 2002a, 2002b).

Let us point out that NE is not an estimate of a latent variable, being different in this respect from the coincident indicators constructed e.g. in Stock and Watson (1989), those routinely produced by OECD and other international organizations, and the currently published Eurocoin. Rather, NE is defined as a real time estimate of the medium to long-run component of GDP growth, and the latter is observable, although with a long delay. As a consequence, the performance of our indicator can be measured. More precisely, the value of the target, which is not available at the end-of-sample time $T$ (the band-pass filter performing very poorly), becomes available with good accuracy at time $T + h$, for a suitable $h$. Therefore our indicator, produced at time $T$, can be compared with the target at $T$ produced at time $T + h$.[1] We believe that these features, an observable target and a measure of performance, represent a substantial improvement over the abovementioned literature.

Our dataset includes monthly series of production prices, wages, share prices, money, unemployment rates, job vacancies, interest rates, exchange rates, industrial production, orders, retail sales, imports, exports, and consumer and business surveys for the euro area countries and the euro area as a whole (see Appendix B for details). The dataset has been organized taking into account the calendar of data releases that is typical in real situations, with the aim of reproducing the staggered flow of information available through time to policy-makers and market forecasters. This lack of synchronism, though little considered in the literature, is crucial for assessing realistically the performance of alternative real-time indicators.[2]

The paper is organized as follows. Section 2 collects some preliminary observations. Section 3 defines our target, i.e. the medium to long-run component of GDP, and discusses its interpretation. Sections 4 and 5 describe and motivate our estimation procedure. Section 6 shows the New Eurocoin indicator, analyzes its real-time performance and compares it with a few alternative indicators. Section 7 concludes. Technical details are presented in Appendix A. Appendix B describes the dataset and data treatment.

# 2 Preliminary observations

To gauge the current state of the economy, given the delay with which GDP is released, market analysts and forecasters resort to more timely and high frequency information and on this basis obtain early estimates of GDP. However, two problems immediately arise: (i) looking at the typical release calendar for the euro area, one can see that timeliness varies greatly even among monthly statistics (end-of-sample unbalance); (ii) since GDP is quarterly we have to handle simultaneously monthly and quarterly data.

Here we combine the comprehensive and non-subjective information provided by GDP

[1] Recent papers providing direct estimates of current activity, as opposed to estimates of latent variables, are Mitchell et al. (2004) and Evans (2005).

[2] Important exceptions are Bernanke and Boivin (2003) and Giannone et. al. (2002).

with the early information provided by surveys and other monthly series to obtain a reliable and timely picture of current economic activity.

Table 1: **The calendar of some macroeconomic series**

| *Time* / *Release date* | DEC. 04 | GEN. 05 | FEB. 05 | MAR. 05 | APR. 05 | MAY 05 | JUN. 05 | | *Delay* |
|---|---|---|---|---|---|---|---|---|---|
| | ***Real time information sets*** | | | | | | | | |
| **GDP** | **Q3 - 2004** | **Q3 - 2004** | **Q4 - 2004** | **Q4 - 2004** | **Q4 - 2004** | **Q1-2005** | **Q1-2005** | | *45-90 days* |
| **Industrial production** | Oct. 04 | Nov. 04 | Dec. 04 | Jan. 05 | Feb. 05 | Mar. 05 | Apr. 05 | | *45-50 days* |
| **Surveys** | Dec. 04 | Jan. 05 | Feb. 05 | Mar. 05 | Apr. 05 | May. 05 | Jun. 05 | | *0-25 days* |
| **Retail sales** | Oct. 04 | Nov. 04 | Dec. 04 | Jan. 05 | Feb. 05 | Mar. 05 | Apr. 05 | | *45-50 days* |
| **Financial markets** | Dec. 04 | Jan. 05 | Feb. 05 | Mar. 05 | Apr. 05 | May. 05 | Jun. 05 | | *0 days* |
| **CPI** | Nov. 04 | Dec. 04 | Jan. 05 | Feb. 05 | Mar. 05 | Apr. 05 | May. 05 | | *15 days* |
| **Car registrations** | Nov. 04 | Dec. 04 | Jan. 05 | Feb. 05 | Mar. 05 | Apr. 05 | May. 05 | | *2-30 days* |
| **Industrial orders** | Oct. 04 | Nov. 04 | Dec. 04 | Jan. 05 | Feb. 05 | Mar. 05 | Apr. 05 | | *50 days* |

As shown in Table 1, Financial Variables and Surveys are the most timely data, while Industrial Production and other "real variables" are usually available with longer delays. Towards the end of month $T$, when we calculate the indicator for the same month $T$, Surveys and Financial Variables are usually observed up to time $T$ (thus with no delay), Car Registration and Industrial Orders up to $T-1$ and Industrial Production indices up to $T-2$ or $T-3$. The GDP series is observed quarterly, so that its delay varies with time. For example, in April only data up to the fourth quarter of the previous year are available, while during the first half of May the delay is reduced as first-quarter preliminary estimates are released.

The most timely variables (such as Purchasing Managers Indexes, Consumer Surveys, Business Climate Indexes, etc.) are usually far from being comprehensive and smooth. Other standard series, such as Industrial Production and Exports, ignore large portions of economic activity and are less timely. Furthermore, all of them exhibit heavy short-run fluctuations and might provide contradictory signals, see Figure 1. As a result, none of them is fully satisfactory and "there is much diversity and uncertainty about which indicators are to be used" (Zarnowitz and Ozyildirim, 2002).

We tackle the end-of-sample unbalance in the following way. Let $x^*_{it}$, $i = 1, \ldots, n$, be the series after outliers and seasonality have been removed and stationarity achieved by

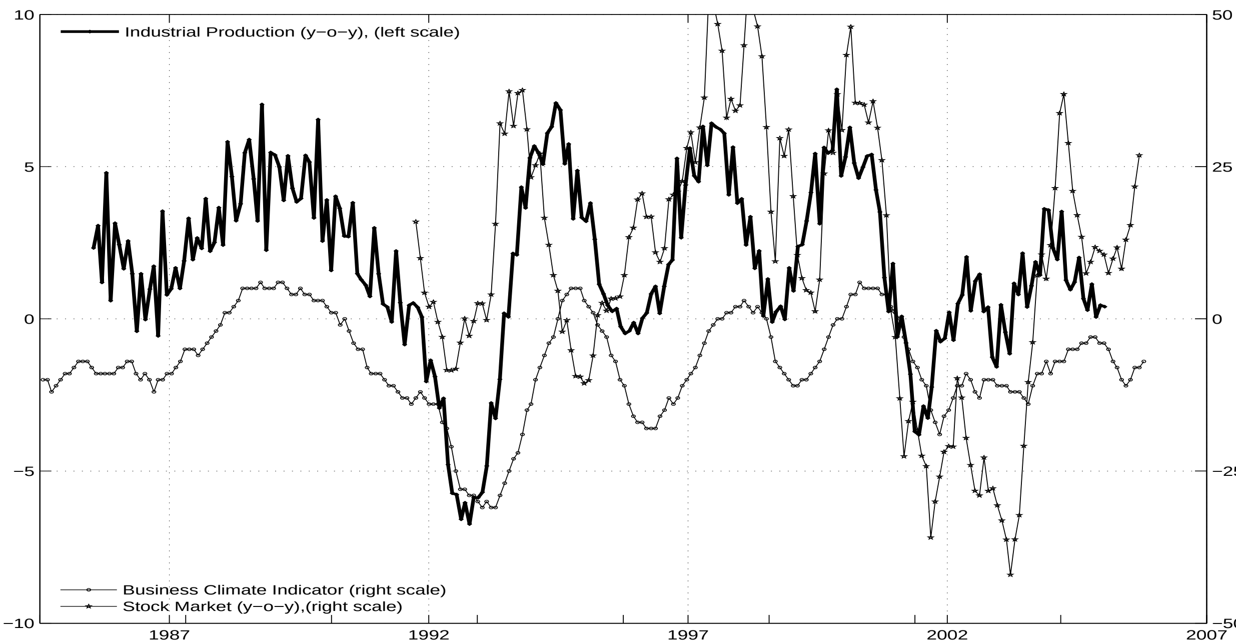


Figure 1: **Some economic indicators for the euro area**

a suitable transformation (see Appendix B). Let $k_i$ be the delivery delay (in months) for variable $x^*_{it}$, so that when we are at the end of the sample its last available observation is $x^*_{i,T-k_i}$.

We define the panel $x_{it}$, $i = 1, \dots, n$, by setting

$$x_{it} = x^*_{i,t-k_i}, \tag{1}$$

so that the last available observation of $x_{it}$ is at $T$ for all $i$. [3]

To use our monthly dataset to obtain a timely GDP indicator it is convenient to think of GDP as a *monthly series of quarterly aggregates with missing observations.* The figure for month $t$, denoted by $z_t$, is defined as the aggregate of GDP for months $t$, $t-1$ and $t-2$, so that there is a two-month overlapping between two subsequent elements of the series. Obviously, the monthly series is observable only for January, March, September and December.

[3]Of course, this realignment implies cutting some observations at the beginning of the sample for several variables. As a result, after transforming and realigning, the dataset begins in May 1987. The same realignment is used both when we consider the whole sample, up to $T$, and when we consider subsamples [1 $\tau$], as in the pseudo real-time exercises carried out in Section 6.

The monthly GDP growth rate is defined as

$$y_t = \log z_t - \log z_{t-3}.$$

Thus $y_t$ is the usual quarter-on-quarter growth rate, except that it is defined for all months.

How to deal with the missing observations in GDP will be discussed in detail in Section 3 and in Appendix A.1.

# 3 The MLRG and its interpretation

A natural way to define the medium to long-run fluctuations of a time series is by considering its spectral decomposition. Assuming stationarity, $y_t$ can be represented as an integral of sine and cosine waves with stochastic weights. This is the well-known *spectral representation* (see e.g. Brockwell and Davis, 1991, ch. 4). We can distinguish long and medium waves, say $c_t$, from short waves, say $s_t$, by splitting the integral into two parts, corresponding to complementary frequency intervals, separated by a threshold value. The choice of the threshold $\pi/6$ is quite natural in our context, since it corresponds to a period of one year: we are not interested in seasonality and other higher frequency waves.

Here we do not delve into the details of the band-pass filter and go directly to the result (see e.g. Baxter and King, 1999, and Christiano and Fitzgerald, 2003). The medium to long-run component $c_t$ is the following infinite, symmetric, two-sided linear combination of the GDP growth series:

$$c_t = \beta(L)y_t = \sum_{k=-\infty}^{\infty} \beta_k y_{t-k}, \quad \beta_k = \begin{cases} \dfrac{\sin(k\pi/6)}{k\pi} & \text{for} \quad k \neq 0 \\ 1/6 \quad \text{for} \quad k = 0. \end{cases} \tag{2}$$

The filter $\beta(L)$ is the low-pass filter which selects waves of frequency smaller than $\pi/6$. Our decomposition is then

$$y_t = c_t + s_t = \beta(L)y_t + [1 - \beta(L)]y_t. \tag{3}$$

Since $\beta(1) = 1$, the mean of the GDP growth series, denoted by $\mu$, is retained in $c_t$ while the mean of $s_t$ is zero. The variance of $y_t$ is broken down into the sum of a short-run variance and a medium to long-run variance, because $c_t$ and $s_t$ are orthogonal. The medium to long-run component $c_t$ is our theoretical target MLRG.

Note that $c_t$ is referred to as "medium to long-run growth" not as growth-rate cycle or "business cycle". Usually, in the definition of a cycle the oscillations of a period longer than 8 years are also removed. This further refinement, though possible in principle, did not seem interesting for our purpose (for different definitions of the cycle, see Stock and Watson, 1999).

Two missing-data problems arise with (2):

(i) Suppose firstly that $y_t$ is observed monthly. Still the filter $\beta(L)$ is infinite, so that within finite samples we can only get approximations of $c_t$. Among different options we chose the following

$$c_t^* = \beta(L) y_t^*, \quad \text{where} \quad y_t^* = \begin{cases} y_t \text{ if } 1 \leq t \leq T \\ \hat{\mu} \text{ if } t < 1 \text{ or } t > T, \end{cases} \tag{4}$$

$\hat{\mu}$ denoting the estimated mean of $y_t$, i.e. the application of the infinite filter $\beta(L)$ to the infinite time series obtained by setting the missing values of $y_t$ equal to its mean. This is, of course, equivalent to a $t$-dependent asymmetric truncation of $\beta(L)$.

(ii) However, as we know, $y_t$ is not observed monthly. Several options are possible, including linear interpolation of the missing values or the more sophisticated techniques introduced in Chow and Lin (1971). However, we should keep in mind that the variable we are interested in is $c_t$ not $y_t$. It turns out that for this purpose the particular interpolation of the missing values in $y_t$ makes no significant difference. This may be easily understood by taking the spectral point of view. Sensible interpolations of the two data point that are missing for each quarter only have effects on the short-run behaviour of the series. Since the short waves are filtered out by $\beta(L)$, the interpolation technique chosen has a negligible effect.

The result of linearly interpolating the missing data in $y_t$, augmenting $y_t$ with its mean, and applying the filter $\beta(L)$, will be denoted by $c_t^*(T)$, or $c_t^*$ when no confusion can arise. In the pseudo real-time exercises presented in Section 6 we will consider subsamples $[1\ \tau]$, with $\tau < T$, and the corresponding series $c_t^*(\tau)$, whose definition is (4) with $\tau$ replacing $T$. Due to its asymmetry, the approximation provided by $c_t^*(T)$ is very poor at the end (and the beginning) of the sample, whereas it is extremely good as soon as $t$ is just twelve months away from $T$ and 1, almost perfect in the centre of the sample. Further details on the construction on $c_t^*$ are given in Appendix A.1.

We henceforth take $c_t^*(T)$, *inside the sample*, as our *target*. Precisely, the performance of NE will be measured by the distance between the value of NE obtained at $t$ and $c_t^*(T)$ with $13 \leq t \leq T - 12$.

Figure 2 presents the approximation $c_t^*(T)$ for euro zone GDP for $13 \leq t \leq T - 12$, along with quarterly GDP growth, $y_t$, where $T$ is August 2005. We see that $c_t^*$ closely

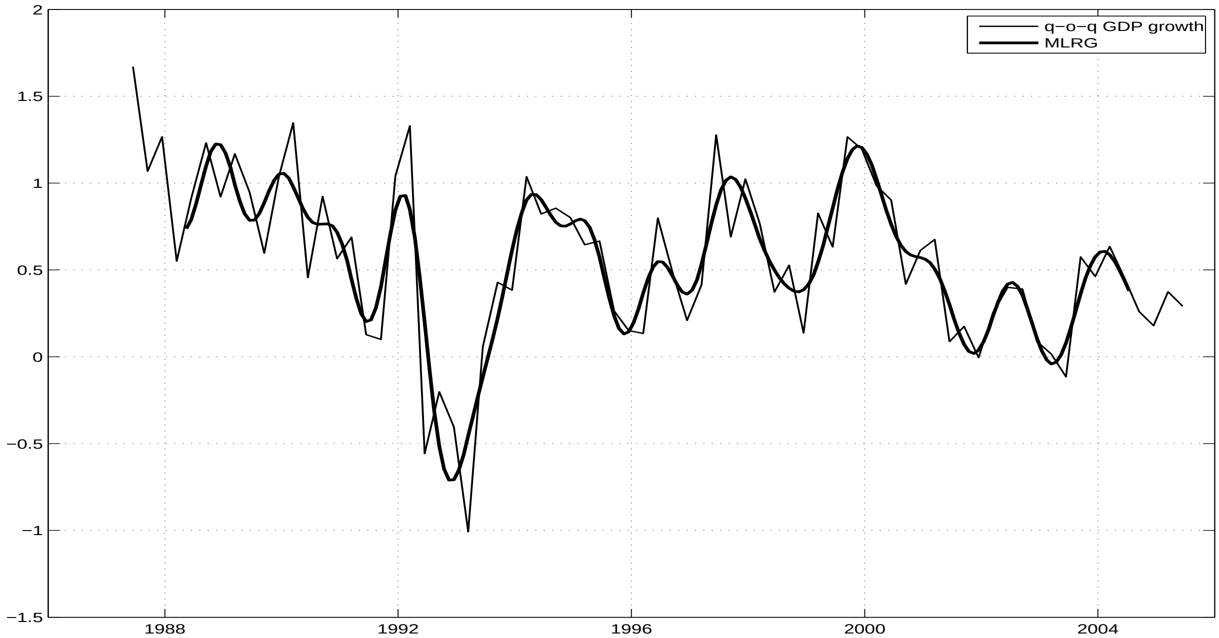


Figure 2: **The (approximate) MLRG, $c_t^*(T)$, and the quarter-on-quarter GDP growth rate**

tracks GDP growth (MLRG captures about 70% of the variance of $y_t$). The main difference between MLRG and GDP growth is that the former, being free from short-run volatility, is far smoother, so that it shows more clearly the underlying growth of the economy. An upturn (downturn) is always followed by several months of decreasing (increasing) growth. As a consequence, observing MLRG in real time, besides being an assessment of the current state of the economy, would provide reliable information about what is going to happen in the near future. This is why a measure of the signal behind the short-lived oscillations is useful for private and public decision-makers.

We conclude this section with a few observations about the relationship between MLRG and the year-on-year change of GDP, which is considered a good measure of medium to long-run growth. Indicating by $\tilde{y}_t$ the year-on-year change of GDP, i.e. the difference between the quarter ending at $t$ and the quarter ending at $t-12$ (divided by 4 to obtain quarterly rates) we have

$$\tilde{y}_t = \frac{y_t + y_{t-3} + y_{t-6} + y_{t-9}}{4}.$$

Hence $\tilde{y}_t$ is a moving average of the $y$ series which, unlike MLRG, is one-sided towards

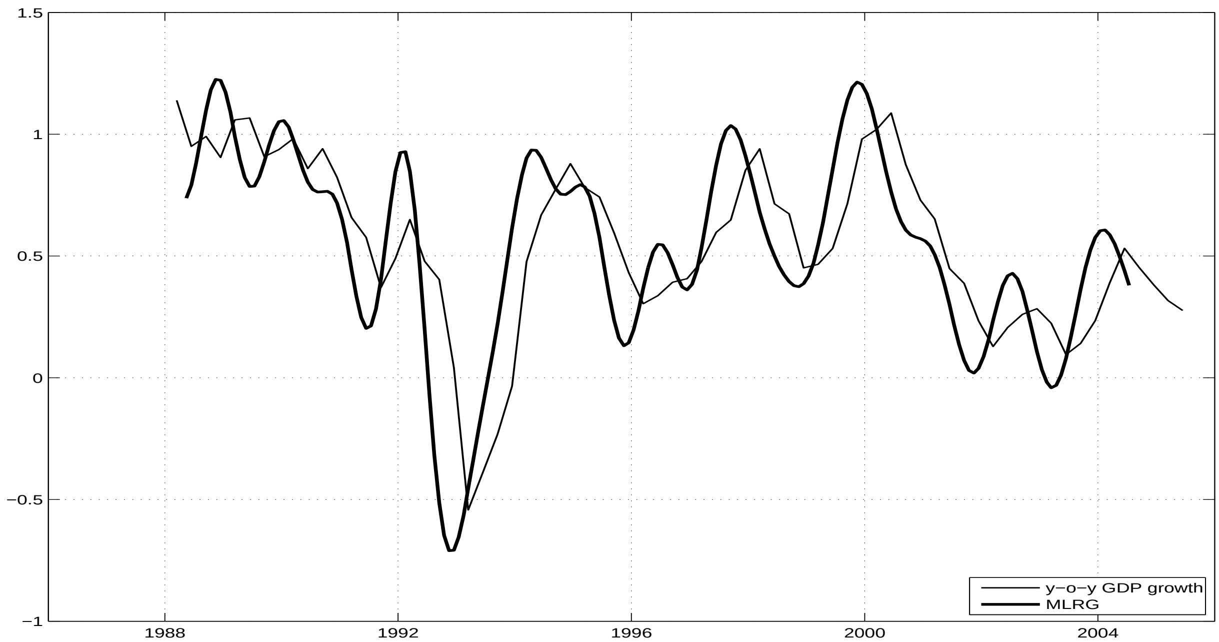


Figure 3: **The (approximate) MLRG and the year-on-year GDP growth rate**

the past and hence not centred at $t$. As a result, $\tilde{y}_t$ is lagging with respect to both $y_t$ and MLRG by several months (precisely four and a half), as is apparent from Figure 3.

The phase shift is reduced if we compare MLRG with the future of $\tilde{y}_t$. In Section 6.4 we show that our indicator, which tracks MLRG, is a good predictor of future year-on-year growth.

# 4 Estimation I: projecting the MLRG on monthly regressors

An obvious consequence of Definition (4) is that at the end of the sample $c_t^*$ is heavily biased toward the sample mean and is therefore ill-suited to provide a good estimate of $c_t$ (this is why in Figures 2 and 3 we cut the first and last year of $c_t^*$).

The end-of-sample bias could in principle be reduced, as suggested by Christiano and Fitzgerald (2003), by projecting $c_t$ onto the available GDP growth data. This provides an alternative to (4), in which the coefficients of the filter depend on the autocovariance

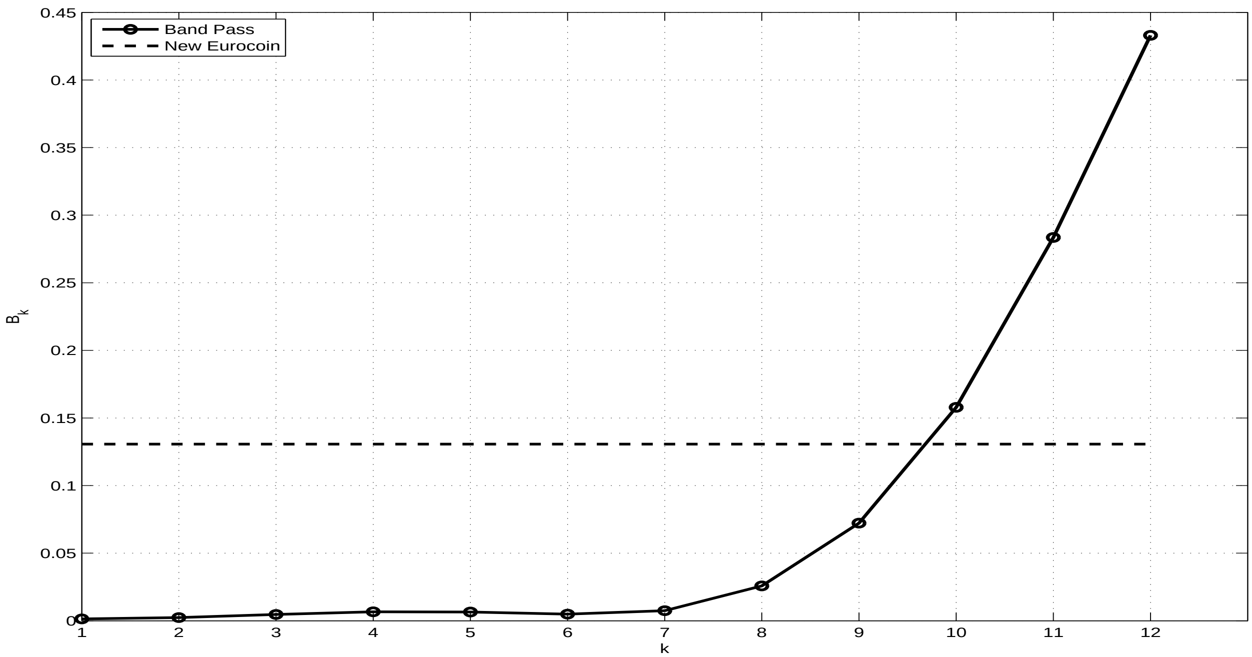


Figure 4: **Estimation of $c_t$: variance of the approximation error using $c_t^*$ (solid line) and NE (dashed line).**

structure of the original series. In the present case, however, this method does not improve upon our filter (see Section 6.2). Valle e Azevedo, Koopman and Rua (2006) propose a multivariate method with band-pass filter properties which exploits information from a relatively small number of variables. We are not far in spirit from their work, the difference being that our procedure is designed to extract information from a large panel of time series.

The main idea underlying NE is that the variables in the dataset that are leading with respect to $y_t$ can be used as proxies for the future values of $y_t$ that are missing at the end of the sample. More precisely, *current values* of lagging, coincident and leading variables in the dataset are used to construct a small number of smooth linear combinations. The latter are then employed as *regressors* to estimate $c_t$. The resulting estimator provides a sizable improvement upon $c_t^*$ at the end of the sample.

This is illustrated in Figure 4, in which some results of Section 6 are anticipated. Within the subsample $[T-81 \;\; T-12]$ we compute $c_t^*(T)$, i.e. the target with no significant end-of-sample bias. Then, for $t$ running from $T-81$ to $T-12$, we compute $c^*_{t-12+k}(t)$, with $k = 1, \ldots, 12$, that is the 12 end-of-sample values of $c^*$ corresponding to the sample $[1\ t]$. The solid line represents the normalized mean square error

$$B_k = \sum_{t=T-81}^{T-12} (c^*_{t-12+k}(t) - c^*_t(T))^2 \Bigg/ \sum_{t=T-81}^{T-12} (c^*_t(T) - \hat{\mu})^2.$$

The level of the dashed line is

$$B = \sum_{t=T-81}^{T-12} (\hat{c}_t(t) - c^*_t(T))^2 \Bigg/ \sum_{t=T-81}^{T-12} (c^*_t(T) - \hat{\mu})^2,$$

where $\hat{c}_t(t)$ is the New Eurocoin indicator obtained at time $t$ using the subsample $[1\ t]$.

We see that $B_k$ is huge at the end of the sample, 40% for $k = 12$, and that NE has a substantial advantage for the last 3 months.

Section 5 deals with the construction of the regressors. Here we give a detailed description of the way we compute the regression once the regressors have been constructed.

Let us assume that our regressors are zero-mean stationary time series $w^m_{kt}$, $k = 1, \ldots, r$, expressed in month-on-month changes or rates of change, just like most of the series in our data-set. Since our target is expressed in quarter-on-quarter variations, we transform the regressors accordingly. This is done by observing that if the flow variable $w^m_{kt}$ is the month-on-month change $W^m_{kt} - W^m_{k,t-1}$, then the corresponding quarter-on-quarter change, $w_{kt} = W^m_{kt} + W^m_{k,t-1} + W^m_{k,t-2} - W^m_{k,t-3} - W^m_{k,t-4} - W^m_{k,t-5}$ is given by

$$w_{kt} = (1 + L + L^2)^2 w^m_{kt}. \tag{5}$$

A similar relation holds approximately for rates of change, with the filter $(1+L+L^2)^2/3$ replacing $(1 + L + L^2)^2$. We use the filter $(1 + L + L^2)^2$ for all regressors, since we are interested in the projection, which is invariant with respect to the scale factor.

The population projection of $c_t$ on the linear space spanned by $w_t = (w_{1t} \ \cdots \ w_{rt})'$ and the constant is

$$P(c_t|w_t) = \mu + \Sigma_{cw}\Sigma_w^{-1} w_t, \tag{6}$$

where $\Sigma_{cw}$ is the row vector whose $k$-th entry is $\mathrm{cov}(c_t, w_{kt})$ and $\Sigma_w$ is the covariance matrix of $w_t$. NE is obtained by replacing the above population moments with estimators:

$$\hat{c}_t = \hat{\mu} + \hat{\Sigma}_{cw}\hat{\Sigma}_w^{-1} w_t. \tag{7}$$

Estimation of $\hat{\Sigma}_w$ is standard once the regressors $w_t$ have been defined, while $\hat{\Sigma}_{cw}$ requires some comments:

(i) The covariances between $c_t$ and $w_t$ can be estimated using $w_t$ and the approximation $c_t^*$, leaving aside end- and beginning-of-sample data.
(ii) Alternatively, we can start by estimating the cross-covariances between the quarterly series $y_t$ and $w_t$. Note that this is possible for any *monthly* lead and lag.[4] Using such cross-covariances we obtain an estimate of the cross-spectrum between $c_t$ and $w_t$, call it $\hat{S}_{cw}(\theta)$. Lastly, $\hat{\Sigma}_{cw}$ is obtained by integrating $\hat{S}_{cw}(\theta)$ over the band $[-\pi/6\ \pi/6]$ (see Appendix A.2 for details).
The results obtained with the two techniques do not differ substantially. The latter is by far the more elegant and has therefore been selected.

# 5 Estimation II: constructing the regressors

The regressors $w_{kt}^m$ will be constructed using techniques from large-dimensional dynamic factor models. We assume that each of the variables $x_{it}$ in the dataset is driven by a small number of common shocks, plus a variable-specific, usually called idiosyncratic, component. The idea that this common-idiosyncratic decomposition provides a useful description of macroeconomic variables goes back to the seminal work of Burns and Mitchell (1946) and has been recently developed in the literature on large-dimensional dynamic factor models; see Bai (2003), Bai and Ng (2002), Forni, Hallin, Lippi and Reichlin (2000, 2001, 2004, 2005; henceforth FHLR), Forni and Lippi (2001), and Stock and Watson (2002a, 2002b), Kapetanios and Marcellino (2004).

Large-dimensional factor models estimate a small (relative to the size of the dataset) number of "common factors", obtained as linear combinations of the $x_{it}$'s, which remove the idiosyncratic components and retain the common sources of variation. The innovation of the present paper with respect to this literature is a procedure to remove both the idiosyncratic and the short-run components, so that the resulting factors are both common and smooth.

Let us firstly recall in some detail the features of the large-dimensional dynamic factor model. We assume that each series in the dataset is the sum of two stationary, mutually orthogonal (at all leads and lags), unobservable components: the *common component*, call it $\chi_{it}$, and the *idiosyncratic component*, $\xi_{it}$:

$$x_{it} = \chi_{it} + \xi_{it}. \tag{8}$$

[4] While it is not possible to estimate a monthly auto-covariance of $y_t$

The common component is driven by a small number, say $q$, of common shocks $u_{ht}$, $h = 1, \dots, q$, which are the same for all the cross-sectional units, but are in general loaded with different coefficients and lag structures:

$$\chi_{it} = b_{i1}(L)u_{1t} + b_{i2}u_{2t} + \cdots + b_{iq}(L)u_{qt}. \tag{9}$$

By contrast, the idiosyncratic components are driven by shocks that are "weakly" correlated across different variables. For simplicity we restrict the model by assuming that $\xi_{it}$ and $\xi_{jt}$ are mutually orthogonal at all leads and lags for $i \neq j$.[5]

Model (8)-(9) will be further specified by assuming that the common components $\chi_{it}$ can be given the static representation

$$\chi_{it} = c_{i1}F_{1t} + c_{i2}F_{2t} + \cdots + c_{ir}F_{rt}. \tag{10}$$

For example, if $q = 2$ and the polynomials $b_{ij}(L)$ are moving averages of order one, then $r = 4$ and

$$(F_{1t}\ F_{2t}\ F_{3t}\ F_{4t}) = (u_{1t}\ u_{1t-1}\ u_{2t}\ u_{2t-1}),$$

we immediately obtain the static representation (10).

Under (10), different consistent estimators have been proposed for the "factors" $F_{jt}$, or, more precisely, for the space $G_F$ spanned by the factors $F_{jt}$. In particular: (i) Stock and Watson (2002a, 2002b) use the first $r$ principal components of the variables $x_{it}$; (ii) FHLR (2005) use a two-step method, producing firstly an estimate of the spectral density matrix of the unobserved components $\chi_{it}$ and $\xi_{it}$, and then use this estimate to obtain the factors by means of generalized principal components. Note that, (i) Stock and Watson's method requires preliminary estimation of the dimension $r$ while (ii) FHLR's method requires estimation of both $q$ and $r$.

The two methods estimate consistently the factor space $G_F$ as both the number of observations in each series ($T$) and the number of series in the dataset ($n$) tend to infinity. Consistent estimates of the common components $\chi_{it}$ are obtained by projecting the variables $x_{it}$ on the estimated factors.

Let us focus on ordinary principal components, i.e. Stock and Watson's estimator. Firstly, using our dataset over the whole sample period $[1\ T]$, the dimension of the factor space $S_F$ has been estimated using the Bai-Ng criteria $\mathrm{PC}_{\mathrm{P1}}$ and $\mathrm{PC}_{\mathrm{P2}}$ (see Bai and Ng, 2002; we set $r_{\max} = 25$), the result being $r = 18$. Secondly, $c_t$ has been projected on the

[5]More details concerning the conditions imposed on the correlation structure of common and idiosyncratic components are found in FHLR (2000).

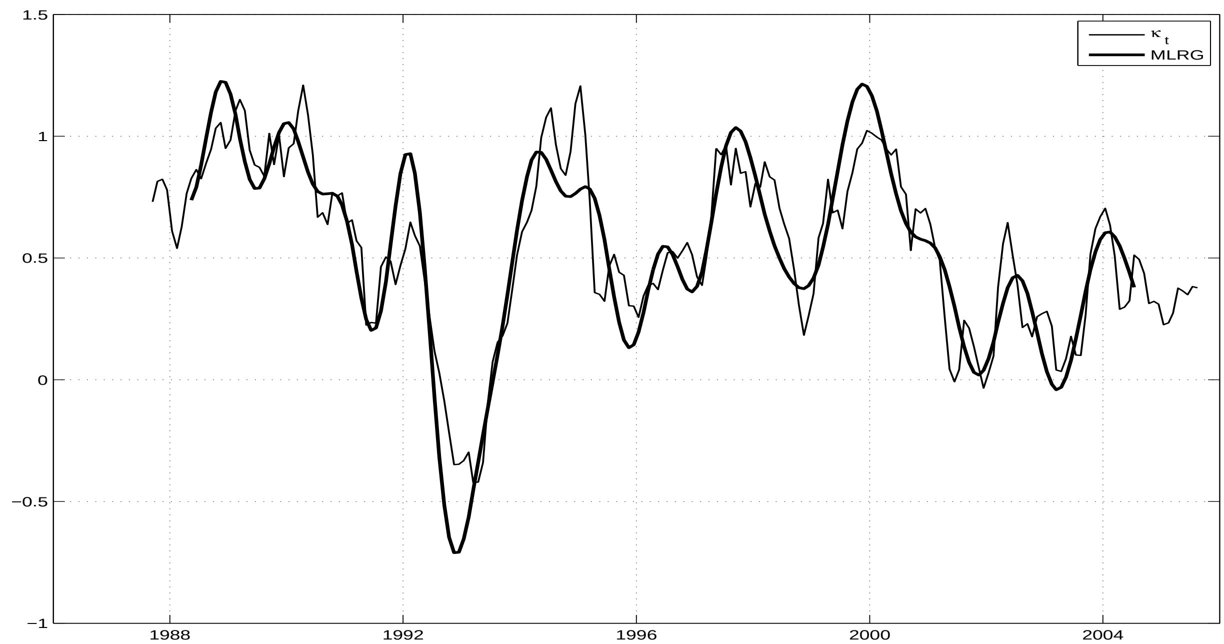


Figure 5: **Principal components estimator and MLRG**

first 18 principal components (filtered with $(1 + L + L^2)^2$, see Section 4), the projection being based on (7).

This projection, denoted by $\kappa_t$,[6] is shown in Figure 5 together with $c_t^*(T)$. Regressing our observable target $c_t^*(T)$ on $\kappa_t$, over the period $[13 \;\; T-12]$, we obtain an $R^2$ as high as 0.93, which is quite remarkable. However, Figure 5 also shows that the projection contains a sizable short-run component. This is not surprising. Ordinary principal components are designed to remove idiosyncratic terms and accomplish this task without any special care for short- or long-run oscillations (an equivalent result has been obtained using the two-step FHLR method).

We claim that by conveniently choosing a basis in $G_F$ (different from the 18 principal components used in the above exercise) we can obtain a projection with approximately the same fit but with a considerably reduced short-run component. Our construction is as follows. Let us go back to representation (8):

$$x_{it} = \chi_{it} + \xi_{it}.$$

[6] We compute $\kappa_t$ only for the whole sample. Therefore we do not need the notation $\kappa_t(T)$.

Corresponding to this decomposition is that of the spectral density matrix of the $x$'s:

$$S_x(\theta) = S_\chi(\theta) + S_\xi(\theta) \tag{11}$$

(remember that the components $\chi_t$ and $\xi_t$ are orthogonal at any lead and lag). Furthermore, the matrix $S_\chi$ can be decomposed into a medium- long-run and a short-run component:

$$S\chi(\theta) = S_\phi(\theta) + S_\psi(\theta), \tag{12}$$

where $S_\phi(\theta) = S_\chi(\theta)$ for $|\theta| < \pi/6$, $S_\phi(\theta) = 0$ for $|\theta| \geq \pi/6$, while $S_\psi(\theta) = S_\chi(\theta) - S_\phi(\theta)$. The matrices $S_\phi$ and $S_\psi$ can be interpreted as the spectral densities resulting from the decomposition of $\chi_t$ into the medium to long-run component $\phi_t = \beta(L)\chi_t$, $\beta(L)$ being the band-pass filter defined in Section 2, and the short-run component $\psi_t = \chi_t - \phi_t$. Integrating (11) and (12) over the interval $[-\pi\ \pi]$, we obtain the following decompositions of the variance-covariance matrix of the $x$'s:

$$\Sigma_x = \Sigma_\chi + \Sigma_\xi = \Sigma_\phi + \Sigma_\psi + \Sigma_\xi. \tag{13}$$

Consistent estimates $\hat{\Sigma}_\chi$, $\hat{\Sigma}_\phi$ and $\hat{\Sigma}_\xi$ can be obtained from the estimates of the spectral densities (see Appendix A.3).

The matrices $\hat{\Sigma}_\chi$, $\hat{\Sigma}_\phi$ and $\hat{\Sigma}_\xi$ are all we need to construct our smooth regressors. We start by determining the linear combination of the variables in the panel that maximizes the variance of the common component in the low-frequency band, i.e. the smoothest linear combination. Then we determine another linear combination with the same property under the constraint of orthogonality to the first, and so on.

Formally, setting $x_t = (x_{1t}\ \cdots\ x_{nt})'$, we look for the vectors $v_k$, $k = 1, \ldots, n$, and the corresponding linear combinations $w^m_{kt} = v'_k x_t$, solving the sequence of maximization problems

$$\max_{v \in R^n}\ v'\hat{\Sigma}_\phi v, \quad \text{s.t. } v'(\hat{\Sigma}_\chi + \hat{\Sigma}_\xi)v = 1, \quad v'\left(\hat{\Sigma}_\chi + \hat{\Sigma}_\xi\right)v_h = 0 \ \text{ for } h < k,$$

where $v_0 = 0$ and $v_h$ solves problem $h$.

The solution of this sequence of problems is given by the *generalized eigenvectors* $v_1, \ldots, v_n$ associated with the *generalized eigenvalues* $\lambda_1, \ldots,\ \lambda_n$, ordered from the largest to the smallest, of the pair of matrices $\left(\hat{\Sigma}_\phi,\ \hat{\Sigma}_\chi + \hat{\Sigma}_\xi\right)$; i.e. the vectors satisfying

$$\hat{\Sigma}_\phi v_k = \lambda_k \left(\hat{\Sigma}_\chi + \hat{\Sigma}_\xi\right) v_k, \tag{14}$$

with the normalization constraints $v_k' \left(\hat{\Sigma}_\chi + \hat{\Sigma}_\xi\right) v_k = 1$ and $v_k' \left(\hat{\Sigma}_\chi + \hat{\Sigma}_\xi\right) v_h = 0$ for $k \neq h$ (see Anderson, 1984, Theorem A.2.4, p. 590). The eigenvalue $\lambda_k$ is equal to the ratio of common-low-frequency to total variance explained by the $k$-th *generalized principal component* $w_{kt}^m$.[7] Of course, this ratio is decreasing with $k$, so that, the greater is $k$, the less smooth and more idiosyncratic is $w_{kt}^m$.

Some comments and clarifying observations are in order.

(a) In the Introduction and in Section 4 we have provided intuition regarding how we obtain intertemporal smoothing using only contemporaneous values of the variables $x_{it}$. Let us be more specific here. Consider the static model

$$x_{it} = b_i u_t + \xi_{it},$$

in which $q = r = 1$. In this case, taking contemporaneous linear combinations of the $x$'s, though removing the idiosyncratic components, does not produce any smoothing. However, if the model were

$$x_{it} = b_i u_{t-k_i} + \xi_{it}, \tag{15}$$

where $k_i$ takes the values 0, 1 or 2, then the first generalized principal component would weigh the $x$'s to obtain the smoothest linear combination of $u_t$, $u_{t-1}$, $u_{t-2}$. Though extremely simplified, model (15) is a fairly good stylization of large macroeconomic datasets, in which the variables $x_{it}$ can be grouped into leading, lagging and central, according to the dynamic loading of the factors. This dynamic heterogeneity of the variables $x_{it}$ is exploited by the generalized principal components to produce intertemporal smoothing.

(b) It is not difficult to show that, given that our model has been specified by (10), the first $r$ generalized principal components approximately span the same space $G_F$ spanned by the first $r$ ordinary principal components (see FHLR, 2005). However, the variable $c_t$, which has to be projected on $G_F$, is by construction very smooth. Therefore its projection on $G_F$ is likely to be well approximated using only the first, and smoothest, generalized principal components. In other words, a fit almost as good as that obtained by the first $r$ ordinary principal components should be obtained by a considerably smoother approximation.

Our procedure can be summarized as follows:

(i) We start by estimating $q$, the dimension of $u_t$ in (9), by means of the criterion proposed in Hallin and Liška (2007). Based on the choice of $q$ we estimate $\hat{S}_\chi(\theta)$ and $\hat{S}_\xi(\theta)$ as in

[7] The generalized principal components used in FHLR (2005) are designed for a different purpose. They are obtained using the generalized eigenvectors of the couple $(\hat{\Sigma}_\chi, \hat{\Sigma}_\xi)$.

FHLR (2000, 2005).
(ii) Then we compute the covariance matrices $\hat{\Sigma}_\chi$, $\hat{\Sigma}_\phi$ and $\hat{\Sigma}_\xi$ as indicated above. We estimate $r$ using Bai and Ng's criterion, compute the generalized eigenvectors $v_k$, $k = 1, \ldots, r$ satisfying (14), and the associated linear combinations $w_{kt}^m = v_k' x_t$.
(iii) Let $\kappa_t^{(s)}$ be the projection of $c_t$ on the first $s$ generalized principal components, while $\kappa_t$, as defined above, is the projection of $c_t$ on the first $r$ principal components (in both cases the principal components are filtered with $(1+L+L^2)^2$, see Section 4; the projection is based on (7)). Then let $\rho$ and $\rho_s$ be the $R^2$'s obtained by projecting $c_t^*$ on $\kappa_t$ and $\kappa_t^{(s)}$ respectively. Starting with $s = 1$, the number of generalized principal components is increased. We stop when the difference between $\rho$ and $\rho_s$ becomes negligible. Call $\overline{s}$ the number of generalized principal components so determined.

The projection of $c_t$ on the first $\overline{s}$ generalized principal components is the New Eurocoin indicator. We use the notation $\hat{c}_t(T)$ for the indicator at time $t$ obtained using the whole sample to estimate the necessary covariance matrices, and $\hat{c}_t(\tau)$ when the subsample $[1 \ \tau]$ is used.

# 6 Results

## 6.1 New Eurocoin indicator

Application of the procedure just described gives:
(i) $q = 2$.
(ii) $r = 18$, see Section 5.
(iii) The fit of the indicator $\kappa_t$, i.e. the $R^2$ of the regression of $c_t^*(T)$ on $\kappa_t$, over the period $[13 \ \ T-12]$, is 0.93 (see again Section 5). The $R^2$ of the regression of $c_t^*(T)$ on $\kappa_t^{(s)}$, with $s$ equal to 1, 3, 5, 6, is 0.77, 0.83, 0.91, 0.93, respectively.[8] The number of slope changes setting $\overline{s} = 6$ is almost half the number of changes of the indicator $\kappa_t$ and almost the same as that obtained setting $\overline{s} = 5$: hence, the improvement of the fit between 5 and 6 is not offset by a reduced smoothness. We therefore select $\overline{s} = 6$ to compute the New Eurocoin indicator $\hat{c}_t$.

[8]The figure 0.93, reported above, is only slightly greater than 0.89, corresponding to the level of the dashed line in Figure 4. Both figures are measures of the performance of NE. However, the first figure (0.93) results from the regression of $c_t^*(T)$ on $\hat{c}_t(T)$, over $[13 \ \ T-12]$, the second figure (0.89) is computed in a pseudo real-time exercise comparing $c_t^*(T)$ and $\hat{c}_t(t)$ over the sample $[T-81 \ \ T-12]$.

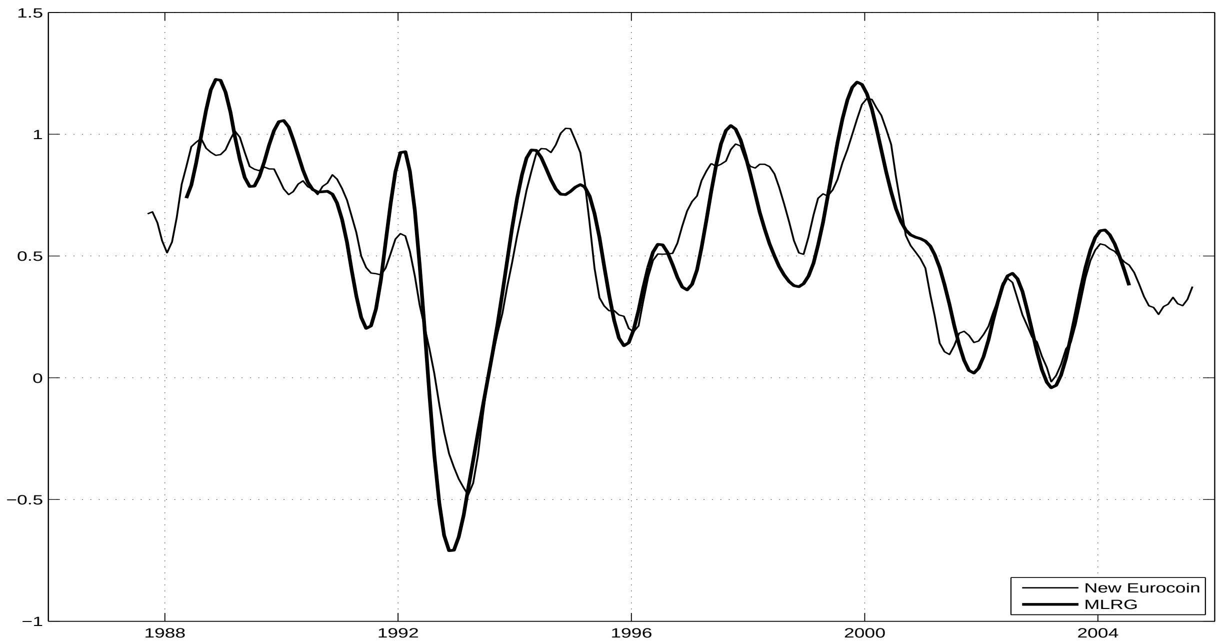


Figure 6: **New Eurocoin and MLRG**

As Figure 6 shows, the phase of New Eurocoin is almost coincident with that of $c_t^*(T)$, which is hardly surprising with an $R^2$ as high as .93.

Figure 7 shows NE (bold solid line) along with two well-known German indices of economic activity: the overall IFO index (dashed line) and the IFO index of business expectations (thin solid line). The IFO indices are normalized in such a way as to have the same mean and variance as NE. The general message of NE and the two IFO indexes is essentially the same. However, there are two important differences. Firstly, our indicator is far less jagged, so that in most cases it correctly signals whether growth is increasing or decreasing. Secondly, the IFO figures have no quantitative interpretation in terms of GDP growth.

## 6.2 The real-time performance

In this subsection we report a pseudo real-time evaluation of NE. Here "pseudo" refers to the fact that we do not use the true real-time preliminary estimates of the GDP, but the final estimates as reported in GDP "vintage" available in September 2005. The same

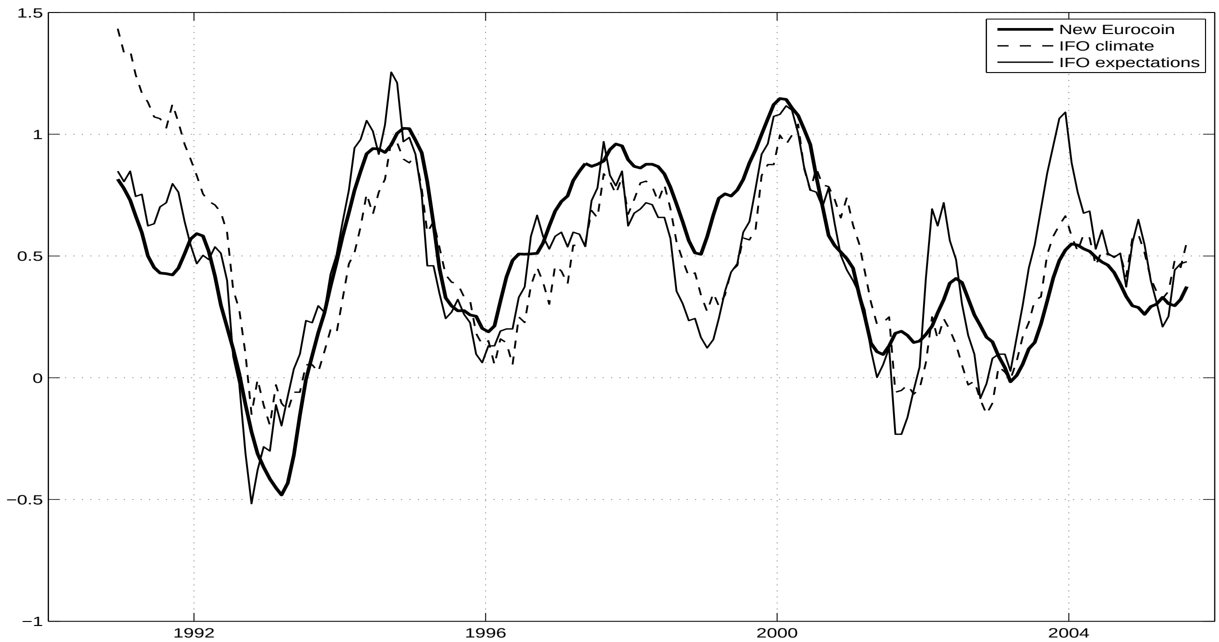


Figure 7: **New Eurocoin and two IFO indices**

holds true for all other monthly variables. Moreover, the exercise is conducted using 6 generalized principal components, the number estimated over the whole sample period $[1\ T]$.

The exercise uses the estimates $\hat{c}_t(t+h)$, that is NE at time $t$ using the data from 1 to $t+h$, $h = 0, 1, 2$, with $t$ running from November 1998 to August 2005.

Figure 8, upper graph, illustrates the results . The long continuous line represents $c_t^*(T)$. The short line ending at $t$ represents the three estimates, $\hat{c}_{t-2}(t)$, $\hat{c}_{t-1}(t)$ and $\hat{c}_t(t)$. Therefore the three points on the short lines over a given $t$ are the first estimate and two revisions of NE at $t$, namely $\hat{c}_t(t)$, $\hat{c}_t(t+1)$ and $\hat{c}_t(t+2)$. Revisions of NE at $t$ are due to re-estimation of the factors and the projection as new data arrive and are modest. The bullets indicate turning points and the diamonds indicate turning point signals (see below for formal definitions).

For comparison, the lower graph shows the end-of-sample estimates obtained by truncating the band-pass filter at the last available GDP observation. Therefore each short line represents $c_{t-2}^*(t)$, $c_{t-1}^*(t)$ and $c_t^*(t)$. Clearly the band-pass filter estimates (BP), although perfectly smooth, exhibit a large bias towards the sample mean. NE estimates

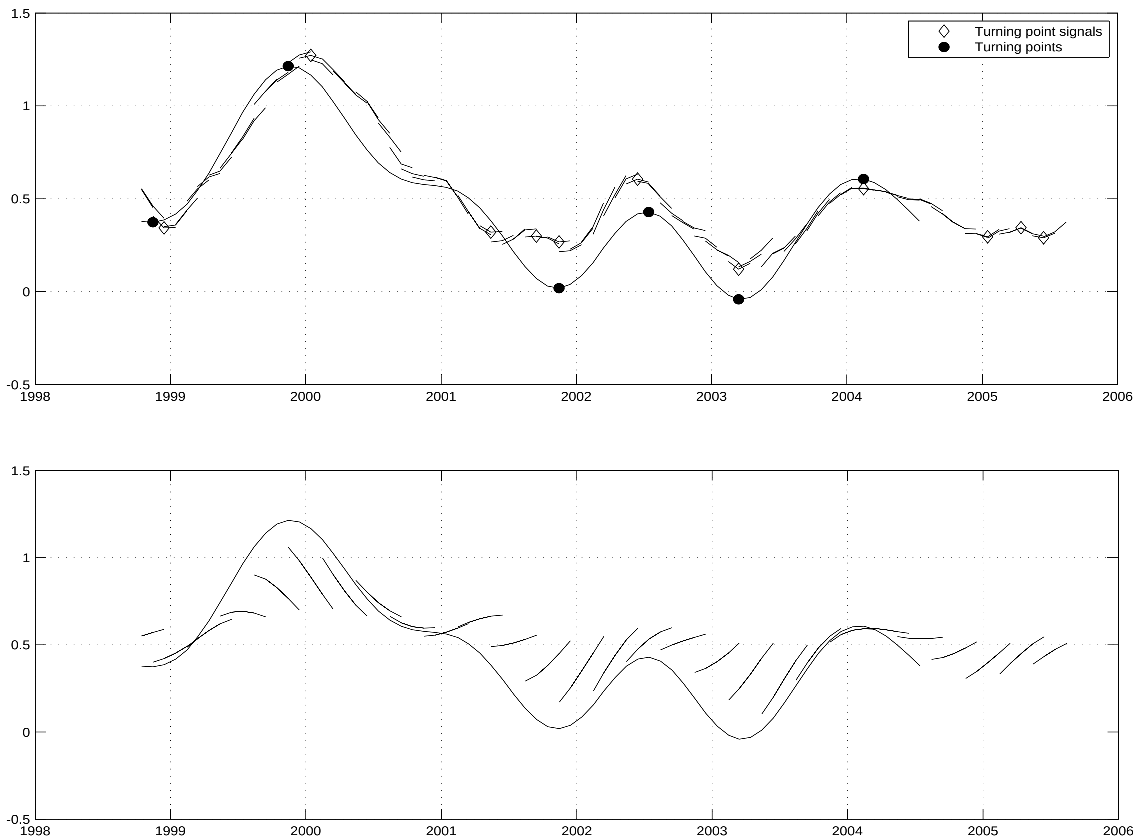


Figure 8: **Pseudo real-time estimates of MLRG, at the end of the sample, obtained with NE (upper panel) and the band-pass filter (BP)**

are more accurate and the revision errors are smaller.

Let us now analyze the results in detail. We are interested in, (a) the ability of $\hat{c}_t(t)$ to approximate (nowcast) $c^*_t(T)$, for the period $T-81 \leq t \leq T-12$, as measured by the root mean-square error $\sqrt{\sum_{t=T-81}^{T-12}[\hat{c}_t(t) - c^*_t(T)]^2/70}$; (b) the ability of $\hat{c}_t(t) - \hat{c}_{t-1}(t) = \Delta\hat{c}_t(t)$ to signal the correct sign of the change, i.e. the sign of $\Delta c^*_t(T)$, as measured by the percentage of correct signs (see Pesaran and Timmermann, 1992); and (c) the size of the revision errors after one month, as measured by the root mean-square deviation $\sum_{t=T-81}^{T-1}[\hat{c}_t(t+1) - \hat{c}_t(t)]^2/81$ (note that as $c^*_t$ is not considered here, we can extend the sample up to $T$).

For comparison with NE, we consider three alternative methods:

(BP) the truncated band-pass filter $c^*_t(t)$;

(ABP) the asymmetric filter proposed by Christiano and Fitzgerald (2003);

(PC) the estimates obtained with ordinary principal components, denoted by $\kappa_t$.

Table 2: **End of sample performance**

| Indicator | Rmse with respect to $c^*$ | % correct signs direction of $c^*$ | Rmse Revision errors |
|---|---|---|---|
| NE | 0.15 | $0.86^\dagger$ | 0.03 |
| BP | 0.27 | 0.57 | 0.09 |
| ABP | 0.31 | 0.59 | 0.08 |
| PC | 0.20 | 0.64 | 0.04 |

Notes: Sample Nov.1998-Aug.2005. The first column reports the RMSE with respect to $c^*$. The second column reports the percentage of correct signs with respect to those of $\Delta c^*$. A (†) indicates that the null of no predictive performance is rejected at 5% significance level (Pesaran Timmerman, 1992). The third column reports the RMSE of the revision errors for the last estimate of NE after one month.

In Table 2 we see that NE scores remarkably better than BP and ABP regarding nowcasting the target $c_t^*$, tracking its direction of change, and in terms of size of revision error (points (a), (b) and (c) above). As expected, PC performs fairly well as far as (a) and (c) are concerned, but is outperformed by NE in terms of tracking the direction of change in the target (b). Hence, NE dominates all other indicators for the criteria we selected.

## 6.3 The behaviour around turning points

The figures in the second column of Table 2, concerning the percentage of correct signs, suggest that NE should perform well in signalling turning points in the target. In the remainder of the present section we explore this issue, but for that purpose, we need precise definitions of turning point, turning point signal and false signal.

To begin with, we define a *turning point* as a slope sign change in our target, $c_t^*(T)$. We have an *upturn (downturn)* at time $t$, if $\Delta c_{t+1}^*(T) = c_{t+1}^*(T) - c_t^*(T)$ is positive (negative), whereas $\Delta c_t^*(T) = c_t^*(T) - c_{t-1}^*(T)$ is negative (positive). According to this definition the target $c_t^*(T)$ exhibits 11 downturns and 10 upturns in the sample (Nov.1998-Aug.2005). In the subsample involved in the pseudo real-time exercise the target exhibits 3 downturns and 3 upturns (see Figure 8).

Next we define a rule to decide when a slope sign change of our indicator $\hat{c}$ can be interpreted as a reliable signal of a turning point in the target $c^*$. To this end, we focus

Table 3: **Classification of signals**

| | $\Delta\hat{c}_{t-2}(t-1)$ | $\Delta\hat{c}_{t-1}(t-1)$ | $\Delta\hat{c}_{t-1}(t)$ | $\Delta\hat{c}_t(t)$ | consistency | signal type |
|---|---|---|---|---|---|---|
| 1 | − | − | − | + | yes | **upturn** at $t-1$ |
| 2 | + | − | − | + | yes | uncertainty |
| 3 | − | − | − | − | yes | deceleration |
| 4 | + | − | − | − | yes | slowdown |
| 5 | + | + | + | − | yes | **downturn** at $t-1$ |
| 6 | − | + | + | − | yes | uncertainty |
| 7 | + | + | + | + | yes | acceleration |
| 8 | − | + | + | + | yes | recovery |
| 9 | − | − | + | − | no | trembling deceleration |
| 10 | + | − | + | − | no | downturn at $t-2$ shifted |
| 11 | − | − | + | + | no | missed upturn |
| 12 | + | − | + | + | no | downturn at $t-2$ not confirmed |
| 13 | + | + | − | + | no | trembling deceleration |
| 14 | − | + | − | + | no | upturn at $t-2$ shifted |
| 15 | + | + | − | − | no | missed downturn |
| 16 | − | + | − | − | no | upturn at $t-2$ not confirmed |

on the sign of the last two changes of the current estimate of our indicator $\hat{c}_t(t)$, and the sign of the last two changes of the previous estimate $\hat{c}_t(t-1)$, that is

$$\text{current estimate:} \qquad \cdots \qquad \Delta\hat{c}_{t-1}(t) \qquad \Delta\hat{c}_t(t) \tag{16}$$

$$\text{previous estimate:} \qquad \Delta\hat{c}_{t-2}(t-1) \qquad \Delta\hat{c}_{t-1}(t-1) \qquad \cdots \tag{17}$$

A sign change between $\Delta\hat{c}_{t-1}(t)$ and $\Delta\hat{c}_t(t)$ makes (16) a candidate as a *signal at $t$ locating a turning point at $t-1$*. However, we accept the sign change in (16) as a turning point signal only if (a) the signal is *consistent*, i.e. the signs of $\Delta\hat{c}_{t-1}(t-1)$ and $\Delta\hat{c}_{t-1}(t)$ coincide, and (b) there is no sign change in (17) between $t-2$ and $t-1$, i.e. the signs of $\Delta\hat{c}_{t-2}(t-1)$ and $\Delta\hat{c}_{t-1}(t-1)$ coincide.

The reason for conditions (a) and (b) is that we want to be strict enough to rule out sign changes that may be caused by unstable estimates rather than by true turning points. Condition (a) is obvious. Condition (b) rules out a sign change between $t-1$ and $t$ that follows the opposite change between $t-2$ and $t-1$ in the previous estimate.

Table 3 lists the 8 possible consistent (rows $1-8$) and the 8 possible inconsistent signals (rows $9-16$) which, in principle, could arise with our indicator. Note that only 2 out of the 8 consistent sign changes in (16) are classified as turning point signals, namely those in the first and the fifth row of Table 3, an upturn and a downturn respectively. Once we have established a rule to identify turning point signals in our indicator we can compare them with turning points that actually occurred in the target.

We say that an upturn (downturn) signal at $t$ locating a turning point at $t-1$ is *false* if $c^*$ has no upturns (downturns) in the interval $[t-3, t+1]$, *correct* otherwise. With this definition, an upturn signal in $\hat{c}_t$ leading or lagging the true upturn (i.e. an upturn in $c_t^*$ by a quarter or more is false, whereas a two-month error is tolerated).

Table 4: **Real time detection of turning points (TP)**

| Target | consistent signals | uncertainty signals | TP signals | TP signals excl. endpoints | Correct TP | % correct TP | % missed TP |
|---|---|---|---|---|---|---|---|
| NE | 81 | 0 | 11 | 8 | 6 | 75 | 0 |
| BP | 81 | 0 | 4 | 4 | 1 | 25 | 83 |
| ABP | 77 | 0 | 3 | 3 | 2 | 67 | 67 |
| PC | 76 | 16 | 17 | 14 | 5 | 36 | 17 |

Notes: Sample Nov.1998-Aug.2005. The first column reports the number of consistent signals (out of 81). The fourth column reports the number of turning point signals when excluding the last 12 signals. The fifth column counts the number of correct turning point signals, i.e. those matching the ones in the target. The last shows the percentage of turning points in the target which are missed by each indicator.

Table 4 shows results for the competing indicators in our real-time exercise. The first signal is missing as the previous estimate is lacking, hence, overall, we have 81 signals. Interestingly, across methods most signals in real time are consistent, all of them for NE and BP, 76 with the indicator based on simple principal components (PC). The latter also provides 16 uncertain signals. Coming to the turning points identified by each indicator (third column), NE indicates 11 turning points, 8 of which identified before the last 12 months, the period over which we cannot compute $c^*$. Among these, 6 correspond to all the turning points in the target. The PC indicator continues to perform poorly, not only in signalling too often a turning point which does not correspond to actual movements in the target, but also missing one of them.

## 6.4 The forecasting properties of the indicator

In Section 3 we argued that we should expect a close match between NE and the GDP growth rate once the latter is smoothed with a moving average such as the one induced by the year-on-year transformation and adjusted for the phase shift.[9] This is confirmed by the results shown in the last two columns of table 5. While the root mean squared error

[9]A similar idea is exploited in Cristadoro et al. (2005) to motivate their result that a core inflation indicator obtained as a smoothed projection of CPI inflation on factors is a good forecaster of the CPI headline inflation.

of NE with respect to quarter-on-quarter GDP growth (first column) is 0.20, the same statistics with respect to year-on-year growth is 0.18 (second column) and decreases to 0.13 and 0.17 when we adjust for the phase shift by considering future year-on-year growth (third and fourth column).[10] None of the competing indicators have similar forecasting properties.

Table 5: **How to relate the monthly indicator to actual GDP growth**

| | RMSE with respect to different growth rates (%) | | | |
|---|---|---|---|---|
| Indicator | quarter-on-quarter current quarter | year-on-year current quarter | year-on-year 1 quarter ahead | year-on-year 2 quarters ahead |
| NE | 0.20 | 0.18 | 0.13 | 0.17 |
| BP | 0.34 | 0.26 | 0.27 | 0.28 |
| ABP | 0.32 | 0.27 | 0.26 | 0.29 |
| PC | 0.21 | 0.20 | 0.17 | 0.21 |

Notes: Sample Nov.1998-Aug.2005.

To better gauge the forecasting ability of NE we compare it with univariate ARMA models of quarterly GDP growth, selected by standard in-sample criteria. Such models are often used as benchmarks in forecasting studies (Stock and Watson, 2002b).

Table 6: **Pseudo real-time forecast performance**

| | Target growth rates (%) | | |
|---|---|---|---|
| Model | quarter-on-quarter current quarter | year-on-year current quarter | year-on-year 1 quarter ahead |
| NE | 0.20 | 0.18 | 0.13 |
| AR (AIC) | 0.35 | 0.19 | 0.25 |
| AR (BIC) | 0.36 | 0.18 | 0.24 |
| ARMA (AIC) | 0.35 | 0.21 | 0.25 |
| ARMA (BIC) | 0.35 | 0.15 | 0.23 |
| Random walk | 0.31 | 0.18 | 0.19 |

Notes: Sample Nov.1998-Aug.2005. The first column reports the root mean square forecast error with respect to *current* quarter-on-quarter GDP growth rate, the second with respect to *current* year-on-year GDP growth rate, the third with respect to *next* quarter year-on-year GDP growth rate. NE is the New Eurocoin forecast obtained using the monthly dataset with information updated at most up to last month of the current quarter. The AR and ARMA models are selected at each step according to their in sample performance (in parenthesis the selection criterion used), and are estimated on the quarterly GDP series.

As shown in Table 6, for quarter-on-quarter GDP growth (first column) and for the

[10]Obviously, we can compare our monthly indicator with actual GDP growth rates only at the end of each quarter.

year-on-year growth rate one quarter ahead (third column) the forecast error of the indicator is far lower than those obtained either with the ARMA or with the random walk.

# 7 Summary and conclusion

Our coincident indicator NE is a timely estimate of the medium to long-run component of euro area GDP growth. The latter, our target, has been defined as a centred, symmetric moving average of GDP growth, whose weights are designed to remove all fluctuations of period shorter than one year. As observed in Section 3, the target, which has a rigorous spectral definition, leads the “popular” measure of medium to long-run change, namely year-on-year GDP growth, by several months.

We avoid the large end-of-sample bias typical of two-sided filters by projecting the target onto suitable linear combinations of a large set of monthly variables. Such linear combinations are designed to discard useless information, namely idiosyncratic and short-run noise, and retain relevant information, i.e. common, cyclical and long-run waves. Both the definition and the estimation of the common, medium to long-run waves are based on recent factor model techniques. Embedding the smoothing into the construction of the regressors is in our opinion an important contribution of the present paper.

The performance of NE as a real-time estimator of the target has been presented in detail in Section 6. The indicator is smooth and easy to interpret. In terms of turning points detection, it scores much better than the competitors that naturally arise as estimators of the medium to long-run component of GDP growth in real time. The reliability of the signal is reinforced by the fact that the revision error of our indicator is extremely small compared with the competitors. We have also shown that NE is a very good forecaster of year-on-year GDP growth 1 and 2 quarters ahead; it also scores well in forecasting quarter-on-quarter GDP growth, with an RMSE of 0.20, which ranks well even in comparison with best practice results.

# Appendix A: Technical details

## A.1 Computing $c_t^*$

The approximation $c_t^*(T)$ is obtained by

$$c_t^*(T) = \hat{\mu} + \beta(L)Y_t, \tag{18}$$

where

$$\hat{\mu} = \sum_{l=1}^{\lfloor T/3 \rfloor} y_{3l-1}/\lfloor T/3 \rfloor \tag{19}$$

and

$$Y_t = \begin{cases} y_t - \hat{\mu} \quad \text{for } t = 3l-1, \quad 1 \leq l \leq \lfloor T/3 \rfloor \\ \frac{2}{3}y_{3l-1} + \frac{1}{3}y_{3l+2} - \hat{\mu} \quad \text{for } t = 3l, \quad 1 \leq l \leq \lfloor T/3 \rfloor - 1 \\ \frac{1}{3}y_{3l-1} + \frac{2}{3}y_{3l+2} - \hat{\mu} \quad \text{for } t = 3l+1, \quad 1 \leq l \leq \lfloor T/3 \rfloor - 1 \\ 0 \quad \text{for } t < 1 \text{ and } t > 3\lfloor T/3 \rfloor - 1. \end{cases}$$

In words, $Y_t$ is obtained by centring (de-meaning) $y_t$, filling the in-sample missing values by linear interpolation and adding zeros outside the sample period. After applying $\beta(L)$ to $Y_t$ we add the estimated mean $\hat{\mu}$, so that the procedure is equivalent to (4). $T$ denotes the last observation available for our monthly series. Note that (18) takes into account the publication delay of the GDP series described in Section 2.

The approximation $c_t^*$ is affected by two sources of errors.
(i) Firstly, as already observed in Section 3, our $c_t^*(T)$ results from a $t$-dependent asymmetric truncation of $\beta(L)$. We can easily compute the approximation error under different assumptions on $y_t$. If $y_t$ is a white noise, for $T = 215$ the mean square approximation error, normalized by the variance of $c_t$, ranges from 0.6% for $t$ in the middle of the sample, to 2.6% for $t = T - 12$. When we take $T - 81$ as sample length, as we do at the beginning of our pseudo real-time exercises, the corresponding figures are 0.9% and 2.7%. Note that the case of a white noise is rather unfavourable. With a positive autocorrelated MA(1) or AR(1), for example, we obtain slightly better results.

Asymmetry has also a phase-effect. This is independent of $y_t$ and can be easily computed. Figure 8 shows the phase of the asymmetric truncation of $\beta(L)$ at $T - 12$, the worst case. More precisely, for each frequency between 0 and $\pi/6$, the figure shows the ratio of the corresponding time delay to the length of the wave. For example, at frequency 0.2, which corresponds to a wave length of $2\,\pi/0.2 = 31.4$ months, the phase delay does

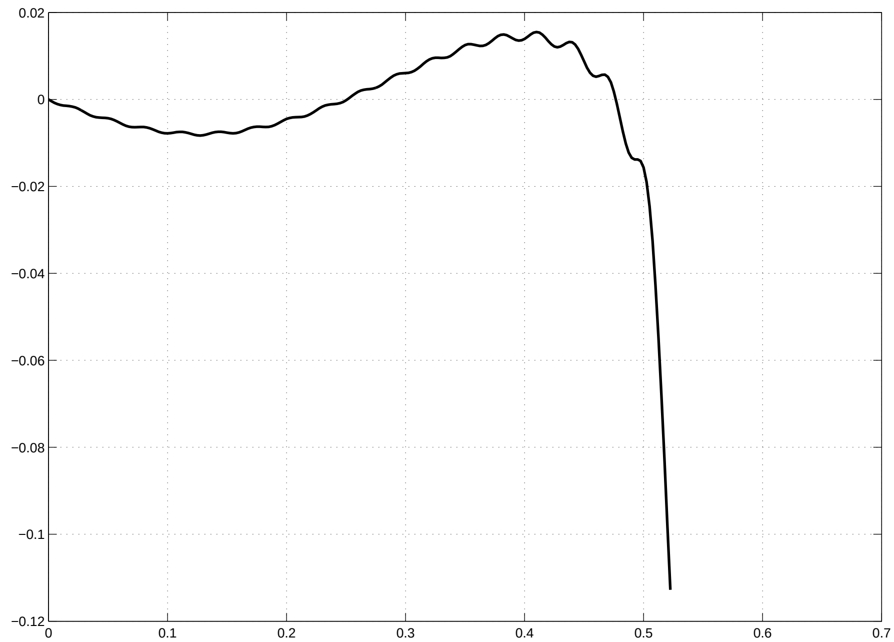


Figure 9: Phase delay at $T - 12$, as a function of the frequency between 0 and $\pi/6$

not reach 1%, that is about 0.3 months. It is only when the frequency approaches $\pi/6$ that the phase delay reaches 10%, that is 1.2 months.
(ii) Secondly, there is an error induced by linear interpolation. Again, the size of the error depends on the unobservable autocorrelation structure of the original series. However, this error is likely to be negligible. Our argument is based on some experiments. We take a monthly series, compute its quarter-on-quarter growth rate $z_t$, compute the linearly interpolated series $Z_t$ (as though $z_t$ were not observable for two months out of each quarter), and compare $\beta(L)z_t$ with $\beta(L)Z_t$. For the industrial production index of the euro zone we obtained a correlation coefficient of 0.9987. Similar results were obtained for other series and by applying Chow and Lin's method instead of linear interpolation. This is hardly surprising. Our monthly quarter-on-quarter growth-rate series have by construction a strong, positive autocorrelation at the first lags, due to overlapping (see Section 2), so that linear interpolation, as well as Chow and Lin's, should not be so far from actual data. The remaining difference is made up of short-run oscillations that, as already argued in Section 3, do not survive application of the filter $\beta(L)$.

In conclusion, (a) At $T - 12$, i.e. in the worst situation, the approximation error and the phase delay are negligible (the first never exceeds 3%), (b) experiments with actual series show that linear interpolation does not make a significant difference on the result of applying $\beta(L)$ to quarter on quarter growth rates, so that $c_t^*$ may be taken as an extremely good approximation of $c_t$ for the interval $13 \leq t \leq T-12$.

## A.2 Estimating $\Sigma_w$ and $\Sigma_{cw}$

As observed in the main text, estimation of $\Sigma_w$ is trivial:

$$\hat{\Sigma}_w = \sum_{t=1}^{T} w_t w_t'/(T-1). \tag{20}$$

Estimation of $\Sigma_{cw}$ is less obvious, since $c_t$ is not observed. We proceed as follows. First, we estimate the covariance of $y_t$ and $w_t$ at lags $k = -M, \dots, M$ as

$$\hat{\Sigma}_{yw}(k) = \sum_{l} y_{3l-1} w'_{3l-1-k}/(\lfloor (T-k)/3 \rfloor - 1), \tag{21}$$

where $l$ varies from $\max[1, 1 + \lfloor (k+1)/3 \rfloor]$ to $\min[\lfloor T/3 \rfloor, \lfloor (T-k)/3 \rfloor]$. Note that the cross-covariances $\Sigma_{yw}(k)$ can be consistently estimated for any lag $k$, despite the fact that $y_t$ is only observed quarterly.

Then, we estimate the cross-spectrum over the relevant frequency interval, at the $2J+1$ equally spaced points $\theta_j$, by using the Bartlett lag-window estimator

$$\hat{S}_{yw}(\theta_j) = \frac{1}{2\pi} \sum_{k=-M}^{M} W_k \, \hat{\Sigma}_{yw}(k) \, e^{-i\theta_j k}, \tag{22}$$

where $W_k = 1 - \frac{|k|}{M+1}$ and $\theta_j = \frac{\pi j}{3(2J+1)}$, $j = -J, \dots, J$. Note that the larger frequency estimated is not $\pi/6$, but the middle point of the $(2J+1)$-th interval, ending at $\pi/6$. Finally, we estimate $\Sigma_{cw}$ by averaging the cross-spectrum over such points, i.e.

$$\hat{\Sigma}_{cw} = \frac{2\pi}{2J+1} \sum_{j=-J}^{J} \hat{S}_{yw}(\theta_j). \tag{23}$$

For New Eurocoin we set $J = 60$ and $M = 24$.

## A.3 Estimating $\Sigma_\phi$, $\Sigma_\chi$ and $\Sigma_\xi$

To get an estimate of $\Sigma_\chi$ we have first to estimate the spectral density matrix of the vector of monthly variables $x_t = (x_{1t} \ \cdots \ x_{nt})'$. We estimate the covariance matrices of

$x_t$ at lags $k = -M, \ldots, M$, as

$$\hat{\Sigma}_x(k) = \sum_t x_t x'_{t-k}/(T-k),$$

where $t$ varies from $\max[1, 1+k]$ to $\min[T, T-k]$. Then we estimate the spectrum of $x_t$ at the $2J+1$ equally spaced frequencies $\theta_j$ by using the Bartlett lag-window estimator

$$\hat{S}_x(\theta_j) = \frac{1}{2\pi} \sum_{l=-M}^{M} W_k \, \hat{\Sigma}_x(k) \, e^{-i\theta_j k}, \tag{24}$$

where $W_k = 1 - \frac{|k|}{M+1}$ and $\theta_j = \frac{2\pi j}{2J+1}$, $j = -J, \ldots, J$. Again we set $J = 60$ and $M = 24$.

As a second step, we compute the eigenvalues and eigenvectors of $\hat{S}_x(\theta)$ at each frequency. Let $\lambda_j(\theta)$ be the $j$-th largest eigenvalue of $\hat{S}_x(\theta)$ and $U_j(\theta)$ be the corresponding eigenvector. Moreover, let $\Lambda(\theta)$ be the $q \times q$ diagonal matrix having on the diagonal the first $q$ eigenvalues in descending order and $U(\theta)$ be the matrix having on the columns the first $q$ eigenvectors, i.e. $U(\theta) = [U_1(\theta) U_2(\theta) \cdots U_q(\theta)]$. Our estimate of $S_\chi$ is

$$\hat{S}_\chi(\theta) = U(\theta)\Lambda(\theta)\tilde{U}(\theta) \tag{25}$$

where tilde denotes conjugation and transposition. Given the correct choice of $q$, consistency results for the entries of this matrix as both $n$ and $T$ go to infinity can easily be obtained from Forni, Hallin, Lippi and Reichlin (2000).

Third, we average $\hat{S}_\chi(\theta)$ over all points $\theta_j$ to get our estimate of $\Sigma_\chi$ and average $\hat{S}_\chi(\theta)$ over the relevant frequency band $[-\frac{2\pi}{12}, \frac{2\pi}{12}]$ to get our estimate of $\Sigma_\phi$:

$$\hat{\Sigma}_\chi = \frac{2\pi}{2J+1} \sum_{j=-J}^{J} \hat{S}_\chi(\theta_j); \tag{26}$$

$$\hat{\Sigma}_\phi = \frac{2\pi}{2J+1} \sum_{j=-10}^{10} \hat{S}_\chi(\theta_j). \tag{27}$$

Finally, our estimate of the idiosyncratic variance-covariance matrix $\Sigma_\xi$ is simply obtained as

$$\hat{\Sigma}_\xi = \operatorname{diag}\left(\hat{\Sigma}_x - \hat{\Sigma}_\chi\right), \tag{28}$$

$\operatorname{diag}(A)$ being the diagonal matrix obtained setting to zero the off-diagonal elements of $A$. This operation is consistent with our assumption of mutual orthogonality of the idiosyncratic components.

## Appendix B: Dataset and treatment

The dataset includes 145 series from Thomson Financial Datastream, referring to the euro area as well as its major economies. [11] For euro area GDP we used data from Fagan et al. (2001) until the first quarter 1991, from then on we used the official Eurostat series (rescaling data prior to 1992 to avoid a sudden change in level). The database is organized into homogeneous blocks, i.e. industrial production indexes (41 series), prices (24), money aggregates (8), interest rates (11), financial variables (6), demand indicators (14), surveys (25), trade variables (9) and labour market series (7).

All series were transformed to remove outliers, seasonal factors and non-stationarity. Regarding outliers, we eliminated from each series those points that were more than 5 standard deviation away from the mean and replaced them with the sample average of the remaining observations. Seasonal adjustment was obtained by regressing variables on a set of seasonal dummies. We did not resort to other more sophisticated procedures (e.g. Seats or X12) to avoid the use of two-sided filters, which would potentially imply large revisions in the seasonally adjusted series. Non-stationarity was removed following an automatic procedure: all the series in a given economic class (e.g. industrial production, prices and so on) were treated in the same way; unit root tests run afterwards confirmed the reasonabless of this choice.

Finally, the series were normalized subtracting the mean and dividing for the standard deviation as usually done in the large factor model literature. The detailed list of the variables and the related transformation are reported in the table below.

[11] The final dataset used in this paper is the result of a search process in a much larger dataset of euro area and national variables. In particular, we looked for series satisfying three main criteria: (i) a sufficient time series span (at least starting in 1987), (ii) with a high correlation and leading property with respect to GDP growth, (iii) released in timely manner by statistical agencies

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## DATA DESCRIPTION

| Group | Description | Type of treatment |
|---|---|---|
| Industrial Production | DE INDUSTRIAL PRODUCTION-INTERMEDIATE GOODS | *(1-L)log* |
| Industrial Production | DE INDUSTRIAL PRODUCTION | *(1-L)log* |
| Industrial Production | DE INDUSTRIAL PRODUCTION-MANUFACTURING | *(1-L)log* |
| Industrial Production | DE INDUSTRIAL PRODN - MANUFACTURE OF CHEMICAL & CHEMICAL PRDS. | *(1-L)log* |
| Industrial Production | DE INDUSTRIAL PRODN. -MANUFACTURE OF RUBBER & PLASTIC PRDS. | *(1-L)log* |
| Industrial Production | DE INDUSTRIAL PRODUCTION-MANUFACTURE OF BASIC METALS | *(1-L)log* |
| Industrial Production | DE INDUSTRIAL PRODN -MANUFACTURE OF ELEC. MACH. & APPARATUS | *(1-L)log* |
| Industrial Production | BG INDUSTRIAL PRODUCTION INCL. CONSTRUCTION | *(1-L)log* |
| Industrial Production | BG INDUSTRIAL PRODUCTION EXCL CONSTRUCTION | *(1-L)log* |
| Industrial Production | BG INDUSTRIAL PRODUCTION-INTERMEDIATE PRODUCTS | *(1-L)log* |
| Industrial Production | BG INDUSTRIAL PRODUCTION-MANUFACTURING | *(1-L)log* |
| Industrial Production | EA INDUSTRIAL PRODUCTION EXCLUDING CONSTRUCTION | *(1-L)log* |
| Industrial Production | EA INDUSTRIAL PRODUCTION-MANUFACTURING | *(1-L)log* |
| Industrial Production | EA INDUSTRIAL PRODN - MANUFACTURE OF PULP, PAPER & PAPER PRD. | *(1-L)log* |
| Industrial Production | EA INDUSTRIAL PRODN - MANUFACTURE OF CHEMICAL & CHEMICAL PRDS. | *(1-L)log* |
| Industrial Production | EA INDUSTRIAL PRODUCTION-MANUFACTURE OF BASIC METALS | *(1-L)log* |
| Industrial Production | EA INDUSTRIAL PRODN -MANUFACTURE OF MACHINERY AND EQUIPMENT | *(1-L)log* |
| Industrial Production | EA INDUSTRIAL PRODUCTION | *(1-L)log* |
| Industrial Production | ES INDUSTRIAL PRODUCTION EXCLUDING CONSTRUCTION | *(1-L)log* |
| Industrial Production | ES INDUSTRIAL PRODUCTION-MANUFACTURING | *(1-L)log* |
| Industrial Production | ES INDUSTRIAL PRODUCTION-MANUFACTURE OF BASIC METALS | *(1-L)log* |
| Industrial Production | ES INDUSTRIAL PRODN -MANUFACTURE OF MACHINERY AND EQUIPMENT | *(1-L)log* |
| Industrial Production | ES INDUSTRIAL PRODUCTION-INTERMEDIATE GOODS | *(1-L)log* |
| Industrial Production | ES INDUSTRIAL PRODUCTION-CAPITAL GOODS | *(1-L)log* |
| Industrial Production | ES INDUSTRIAL PRODUCTION-OTHER NON | *(1-L)log* |
| Industrial Production | FN INDUSTRIAL PRODUCTION EXCLUDING CONSTRUCTION | *(1-L)log* |
| Industrial Production | FR INDUDSTRIAL PRODUCTION (UUSTED) | *(1-L)log* |
| Industrial Production | FR INDUSTRIAL PRODUCTION-MANUFACTURING | *(1-L)log* |
| Industrial Production | FR INDUSTRIAL PRODUCTION-CONSUMER GOODS | *(1-L)log* |
| Industrial Production | FR INDUSTRIAL PRODUCTION-ENERGY PRODUCTS | *(1-L)log* |
| Industrial Production | FR INDUSTRIAL PRODUCTION-INVESTMENT GOODS | *(1-L)log* |
| Industrial Production | FR INDUSTRIAL PRODUCTION-MANUFACTURING | *(1-L)log* |
| Industrial Production | IR INDUSTRIAL PRODUCTION-MANUFACTURING | *(1-L)log* |
| Industrial Production | IR INDUSTRIAL PRODUCTION-INDUSTRIES | *(1-L)log* |
| Industrial Production | IT INDUSTRIAL PRODUCTION EXCLUDING CONSTRUCTION | *(1-L)log* |
| Industrial Production | IT INDUSTRIAL PRODUCTION: CONSUMER GOODS | *(1-L)log* |
| Industrial Production | IT INDUSTRIAL PRODUCTION: INVESTMENT GOODS | *(1-L)log* |
| Industrial Production | IT INDUSTRIAL PRODUCTION | *(1-L)log* |
| Industrial Production | NL INDUSTRIAL PRODUCTION EXCLUDING CONSTRUCTION | *(1-L)log* |
| Industrial Production | NL INDUSTRIAL PRODUCTION | *(1-L)log* |
| Industrial Production | PT INDUSTRIAL PRODUCTION (ADJUSTED FOR WORKING DAYS) | *(1-L)log* |
| Prices | DE PPI: ENERGY | *(1-L)log* |
| Prices | DE PPI: INDUSTRY (EXCLUDINGCONSTRUCTION) | *(1-L)log* |
| Prices | DE PPI: MANUFACTURING | *(1-L)log* |
| Prices | DE PPI: NON - DURABLE CONSUMER GOODS | *(1-L)log* |
| Prices | DE PPI: INDUSTRIAL PRODUCTS | *(1-L)log* |
| Prices | BG PPI: DURABLE CONSUMER GOODS | *(1-L)log* |
| Prices | BG PPI: ENERGY | *(1-L)log* |
| Prices | BG PPI: INDUSTRY (EXCLUDINGCONSTRUCTION) | *(1-L)log* |
| Prices | BG PPI: MANUFACTURING | *(1-L)log* |
| Prices | EA PPI: TOTAL MANUFACTURING -DOMESTIC MARKET | *(1-L)log* |
| Prices | EA CPI (DS CALCULATED BEFORE 1990, HARMONISED) | *(1-L)log* |
| Prices | EA INDUSTRIAL PPI-EXCLUDING CONSTRUCTION | *(1-L)log* |
| Prices | ES PPI: DURABLE CONSUMER GOODS | *(1-L)log* |
| Prices | ES PPI: ENERGY | *(1-L)log* |
| Prices | ES PPI: INDUSTRY (EXCLUDINGCONSTRUCTION) | *(1-L)log* |
| Prices | ES PPI: MANUFACTURING | *(1-L)log* |
| Prices | ES PPI: NON - DURABLE CONSUMER GOODS | *(1-L)log* |
| Prices | FN PPI: INDUSTRY (EXCLUDING CONSTRUCTION) | *(1-L)log* |
| Prices | GR PPI: MANUFACTURING | *(1-L)log* |
| Prices | IR PPI: INDUSTRY (EXCLUDING CONSTRUCTION) | *(1-L)log* |
| Prices | IT PPI: ENERGY | *(1-L)log* |
| Prices | IT PPI: NON - DURABLE CONSUMER GOODS | *(1-L)log* |
| Prices | NL PPI-MANUFACTURED GOODS | *(1-L)log* |
| Prices | NL PPI-INTERMEDIATE GOODS OUTPUT | *(1-L)log* |
| Trade | DE EXPORTS FOB | *(1-L)log* |
| Trade | DE IMPORTS CIF | *(1-L)log* |
| Trade | BG EXPORTS (FOB) | *(1-L)log* |
| Trade | BG IMPORTS (CIF) | *(1-L)log* |
| Trade | ES EXPORTS FOB | *(1-L)log* |
| Trade | ES IMPORTS CIF | *(1-L)log* |
| Trade | FR EXPORTS FOB | *(1-L)log* |
| Trade | IT EXPORTS FOB | *(1-L)log* |
| Trade | NL IMPORTS (CIF) | *(1-L)log* |

**DATA DESCRIPTION** (*continued*)

| Group | Description | Type of treatment |
|---|---|---|
| Surveys | DE CONSUMER SURVEY: MAJOR PURCH.OVER NEXT 12 MONTHS - GERMANY | -- |
| Surveys | DE INDUSTRY SURVEY: ORDER BOOK POSITION-GERMANY | -- |
| Surveys | BG INDUSTRIAL CONFIDENCE INDICATOR-BELGIUM | -- |
| Surveys | BG INDUSTRY SURVEY: ORDER BOOK POSITION-BELGIUM | -- |
| Surveys | ES CONSUMER SURVEY: MAJOR PURCH.OVER NEXT 12 MONTHS-SPAIN | -- |
| Surveys | ES ECONOMIC SENTIMENT INDICATOR-SPAIN | -- |
| Surveys | ES INDUSTRY SURVEY: ORDER BOOK POSITION-SPAIN | -- |
| Surveys | ES INDUSTRY SURVEY: PROD.EXPECTATION FOR MTH. AHEAD-SPAIN | -- |
| Surveys | FR CONSTRUCTION CONFIDENCE INDICATOR-FRANCE | -- |
| Surveys | FR INDUSTRIAL CONFIDENCE INDICATOR-FRANCE | -- |
| Surveys | FR SURVEY: INDUSTRY-ORDERBOOK & DEMAND | -- |
| Surveys | FR SURVEY: MANUFACTURING OUTPUT LEVEL-GENERAL OUTLOOK | -- |
| Surveys | FR SURVEY: INDUSTRY-RECENT OUTPUT TREND | -- |
| Surveys | FR SURVEY: INDUSTRY-PROBABLE OUTPUT TREND | -- |
| Surveys | IT ISAE HOUSEHOLD CONFIDENCE INDEX: NET OF IRREGULAR COMPONENTS | -- |
| Surveys | IT CONSUMER CONFIDENCE INDICATOR-ITALY | -- |
| Surveys | IT INDUSTRY SURVEY: STOCKS OF FINISHED GOODS-ITALY | -- |
| Surveys | IT INDUSTRY SURVEY: PROD.EXPECTATION FOR MTH. AHEAD-ITALY | -- |
| Surveys | NL CONSUMER SURVEY: ECONOMIC SITUATION LAST 12 MTH - NETHERLANDS | -- |
| Surveys | DE ASSESSMENT OF BUSINESS SITUATION: CONSTRUCTION | -- |
| Surveys | DE ASSESSMENT OF BUSINESS SITUATION | -- |
| Surveys | DE BUSINESS EXPECTATIONS | -- |
| Surveys | DE ASSESSMENT OF BUSINESS SITUATION: MANUFACTURING | -- |
| Surveys | DE BUSINESS CLIMATE INDEX: MANUFACTURING | -- |
| Surveys | DE ASSESSMENT OF BUSINESS SITUATION: TRADE | -- |
| Interest Rates | DE MONEY MARKET RATE ( FEDERAL FUNDS ) | *(1-L)* |
| Interest Rates | DE GOVT BOND YIELD-LONGTERM | *(1-L)* |
| Interest Rates | DE MORTGAGE BANK LENDING TODOMESTIC NON - BANKS | *(1-L)log* |
| Interest Rates | BG CENTRAL GOVERNMENT BOND-5 YEAR YIELD | -- |
| Interest Rates | BG TREASURY BILL RATE | *(1-L)* |
| Interest Rates | FN MONEY MARKET RATE ( FEDERAL FUNDS ) | *(1-L)* |
| Interest Rates | FR MONEY MARKET INT.RATES -AVERAGE YEARLY MONEY MARKET RATE | *(1-L)* |
| Interest Rates | GR TREASURY BILL RATE | *(1-L)* |
| Interest Rates | IT TREASURY BOND NET YIELD- SECONDARY MKT. (EP) | *(1-L)* |
| Interest Rates | NL LENDING RATE (PRIME RATE) | *(1-L)* |
| Interest Rates | NL GOVT BOND YIELD-LONGTERM | *(1-L)* |
| Wages | DE UNIT LABOUR COSTS, RELATIVE NORMALIZED | *(1-L)log* |
| Wages | DE WAGE & SALARY RATES: MONTHLY - PRODUCING SECTOR(PAN DE M0191) | *(1-L)log* |
| Wages | IT HOURLY RATES IN INDUSTRY | *(1-L)log* |
| Wages | NL HOURLY WAGE RATE MANUFACTURING | *(1-L)log* |
| Money Supply | DE MONEY SUPPLY-M2 (CONTINUOUS SERIES) | *(1-L)log* |
| Money Supply | DE MONEY SUPPLY-M3 (CONTINUOUS SERIES) | *(1-L)log* |
| Money Supply | EA MONEY SUPPLY: M1 | *(1-L)log* |
| Money Supply | EA MONEY SUPPLY: M3 | *(1-L)log* |
| Money Supply | FR MONEY SUPPLY-M1 (NATIONAL CONTRIBUTION TO M1) | *(1-L)log* |
| Money Supply | FR MONEY SUPPLY-M3 (NATIONAL CONTRIBUTION TO M3) | *(1-L)log* |
| Money Supply | IT MONEY SUPPLY: M1-ITALIAN CONTRIBUTION TO THE EURO AREA | *(1-L)log* |
| Money Supply | IT MONEY SUPPLY: M3-ITALIAN CONTRIBUTION TO THE EURO AREA | *(1-L)log* |
| Exchange Rates | DE REAL EFFECTIVE EXCHANGE RATES | *(1-L)* |
| Exchange Rates | EA U.S. $ TO 1 EURO (ECU PRIOR TO 1999) | *(1-L)* |
| Exchange Rates | IT REAL EFFECTIVE EXCHANGE RATES | *(1-L)* |
| Finance | FR SHARE PRICES-SBF 250 | *(1-L)log* |
| Finance | US STANDARD AND POORS COMPOSITE INDEX (EP) | *(1-L)log* |
| Finance | US DOW JONES INDUSTRIALS SHARE PRICE INDEX (EP) | *(1-L)log* |
| Demand Indicators | DE RETAIL SALES EXCLUDING CARS (DERETT0TF FOR 2000=100) | *(1-L)log* |
| Demand Indicators | DE VACANCIES (PAN DE FROM JAN 1994) | *(1-L)* |
| Demand Indicators | DE WHOLE SALES TURN OVER, NOMINAL VALUE | *(1-L)log* |
| Demand Indicators | BG NEW CAR REGISTRATIONS | *(1-L)log* |
| Demand Indicators | BG RETAIL SALES | *(1-L)log* |
| Demand Indicators | BG RETAIL SALES-FOOD | *(1-L)log* |
| Demand Indicators | ES EMPLOYMENT PROMOTION CONTRACTS: IN PRACTICE | *(1-L)* |
| Demand Indicators | ES NEW CAR REGISTRATIONS | *(1-L)log* |
| Demand Indicators | FR NEW CAR REGISTRATIONS | *(1-L)log* |
| Demand Indicators | FR HOUSEHOLD CONSUMPTION-DURABLE GOODS | *(1-L)log* |
| Demand Indicators | FR HOUSEHOLD CONSUMPTION-MANUFACTURED GOODS, RETAIL GOODS | *(1-L)log* |
| Demand Indicators | FR HOUSEHOLD CONSUMPTION-MANUFACTURED GOODS | *(1-L)log* |
| Demand Indicators | IT NEW CAR REGISTRATIONS | *(1-L)log* |
| Demand Indicators | IT RETAIL SALES | *(1-L)log* |
| Unemployment | DE STANDARDIZED UNEMPLOYMENT RATE | *(1-L)* |
| Unemployment | FR UNEMPLOYMENT RATE-UNDER 25 YEARS | *(1-L)* |
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