

Monthly Forecasts of the Euro zone GDP by Means of a Coincident Index

Stime Mensili del PIL della zona Euro attraverso un Indicatore Coincidente

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Riassunto: Il lavoro presenta un possibile approccio per il calcolo di una stima preliminare del PIL mensile della zona Euro attraverso un indicatore sintetico costruito sulla base di statistiche congiunturali quantitative e qualitative rilevate nell'area e disponibili entro 45-50 giorni dalla fine del mese di riferimento. L'indicatore viene calcolato mediante l'aggregazione della stima delle componenti comuni estratte dall'insieme delle variabili raccolte attraverso l'utilizzo di modelli fattoriali dinamici generalizzati. Per il metodo di costruzione adottato, tale indice può essere considerato coincidente rispetto al ciclo economico dell'area Euro. Le stime dei tassi di crescita mensili del PIL vengono quindi ricavate attraverso un modello di disaggregazione temporale dei tassi di crescita trimestrali.

Keywords: Generalized dynamic factor models, coincident index, temporal disaggregation methods, flash estimates.

1. Introduction

The process of economic and monetary unification of the European countries makes more and more important the analysis of the state of the economy at the Euro zone level. The growing availability of official statistics for the whole zone¹ enables researchers to build econometric models directly for the Euro GDP, which certainly represents a key variable for the economy. The usefulness of such models for short-term analysis is strictly connected to the frequency and timeliness with which exogenous variables are available.

This paper proposes a direct solution for the problem of obtaining preliminary estimates of the monthly growth rate of the Euro zone GDP. A large panel of monthly observed indicators for the Euro zone, available within 45-50 days from the end of the reference month, is collected. A common signal for each of these indicators is estimated by means of generalized dynamic factor models, following the approach proposed in Forni, Hallin, Lippi and Reichlin (1999). Then, the coincident index is worked out as aggregation of the common components of those indicators which are found in phase with respect to the European GDP. Such coincident index is used to derive a monthly dynamic of the GDP by using a time disaggregation technique. The disaggregation model is based on a dynamic version of the famous Chow and Lin's solution, as proposed in Santos Silva and Cardoso (2001) in the version revised and corrected by Di Fonzo (2001).

¹Aggregated statistics for the Euro zone are generally derived as aggregation of basic data from member states and are periodically released by European institutions, such as Eurostat, ECB and DG-ECFIN.

The following section describes the procedure of construction of the coincident index based on the generalized dynamic factor model's approach. In section 3 we derive a dynamic specification for $\Delta_4 gdp_t$, a variable which approximates the four-quarter growth rate of the Euro GDP. The disaggregation method used allows us to forecast the twelve-month growth rate by extrapolation. Finally, we compare the official quarterly figures $\Delta_4 gdp_t$ with the quarterly forecasts resulted by the estimated model (obtained in aggregation mean of the monthly forecasts) for the period 00:Q1-01:Q2.

2. A coincident index for the Euro zone

There exist several economic indicators that might be used to model the Euro GDP. The selection is generally led by researchers on the basis of both theoretical and empirical considerations. This kind of approach may hide several snares. Firstly, there is the risk that models are too dependent from the economic theory. Second, the empirical relationships between variables may evolve during time, especially in case of structural changes in the economy. This would require a continuous process of upgrading and correction of the model specification.

An alternative strategy is to employ some automatic means of data reduction of large amount of feasible indicators into few non-observable variables which capture most of the variance in the panel. Such variables (generally called factors) affect all the observed series and, taken together, they can be interpreted as a sort of business cycle proxy.

In this paper we use a procedure based on the dynamic factor models, which have been introduced in literature by Sargent and Sims (1977). Forni, Hallin, Lippi and Reichlin (2000) generalized this kind of models, allowing for non-orthogonal idiosyncratic components. The method proposed in Forni, Hallin, Lippi and Reichlin (1999) is adapted to this context. The $n \times 1$ vector of stationary variables² $\mathbf{x}_{nt} = (x_{1t}, x_{2t}, \dots, x_{nt})$ can be expressed as the sum of two orthogonal components

$$\mathbf{x}_{nt} = \boldsymbol{\chi}_{nt} + \boldsymbol{\xi}_{nt} \quad (1)$$

where $\boldsymbol{\chi}_{nt}$ and $\boldsymbol{\xi}_{nt}$ represent the common components and the idiosyncratic components of $\mathbf{x}_{nt}$, respectively. For each variables of $\mathbf{x}_{nt}$, the common component can be considered as the part of the original signal which is highly correlated with the common components of the remaining variables in the dataset. The common components are calculated as the projections of the observations onto the leads and lags of the dynamic principal components of the observations and the idiosyncratic components are derived as the orthogonal residuals.

Using the estimate of the spectral density matrix $\hat{\boldsymbol{\Sigma}}^x(\theta)$, we are able to classify whether an indicator is coincident, lagging or leading with respect to the Euro business cycle. In particular, we compute the cross-spectral density between the common components of $\mathbf{B}x_{jt}$ and $\Delta_4 gdp_t$, which is taken as the reference variable for the Euro economy, where $\mathbf{B}$ is a transformation matrix $t \times 3t$ that yields t quarterly figures as averages of the corresponding $3t$ monthly figures. The argument ω_{jt} of these densities at frequency $\theta^* = \pi/8$, which corresponds to a cycle of a period of four years, represents the phase angle delay with respect to the Euro area GDP: hence, we classify the j -th indicator as

²Non-stationary variables can be treated with such model after making them stationary with differencing or detrending.

coincident if $|\omega_{jt}(\theta^*)|$ is smaller than the prespecified angle phase lead $\tau = \pi/48$, corresponding to a period of one month (0.33 quarters).

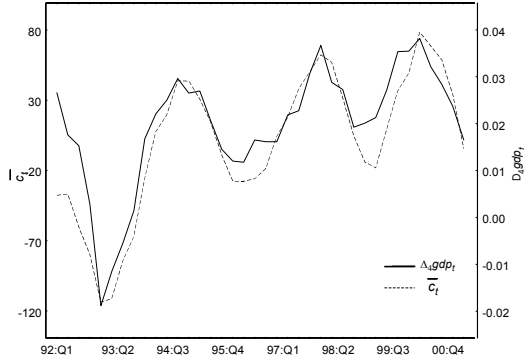
The coincident index c_t is computed as the average of the common components of the coincident indicators through the formula

$$c_t = \sum_{j \in C} \hat{r}_j^2 (2\pi - \omega_{jt}) \chi_{jt} \quad (2)$$

where C is the set of the coincident indicators and $\hat{r}_j$ the estimated correlation coefficient between the common components of $\mathbf{B}x_{jt}$ and $\Delta_4 gdp_t$.

A panel of monthly economic indicators for the Euro area is collected, among which a large amount of variables extracted from the qualitative surveys, industrial production index, new passenger car registration and retail sales index (about 30 variables). The average ‘degree of commonality’, measured by the variance ratios of the common components variability compared to the total, is equal to 0.86, with a standard deviation of 0.13. About one-fourth of the variables in the panel are found to be in phase, among which three-four qualitative balances of business and consumer surveys. Figure 1 shows the high level of correlation between $\Delta_4 gdp_t$ and $\bar{c}_t$, with $\bar{c}_t = \mathbf{B}c_t$.

Figure 1: $\Delta_4 gdp_t$ and $\bar{c}_t$ over the period 92:Q1 - 01:Q2



3. Monthly forecasts of the Euro zone GDP

The monthly coincident index c_t is promptly computable within 45-50 days after the end of the month. Given the high level of correlation of $\bar{c}_t$ with respect to $\Delta_4 gdp_t$, it can conveniently be exploited in the estimation of a monthly dynamic for the Euro GDP. Furthermore, it can also be used to forecast the unknown current period.

The following dynamic specification for $\Delta_4 gdp_t$ ³

$$\Delta_4 gdp_t = \alpha + \phi \Delta_4 gdp_{t-1} + \beta_1 \bar{c}_t + \beta_2 \bar{c}_{t-1} + \gamma D931 \quad (3)$$

is estimated for the period 92:Q2 to 01:Q2, with a dummy variable ($D931$) for the quarter 93:Q1. Table 1 shows the estimated coefficient for Eq. (3); the R^2 is equal to 0.95 and all the estimated diagnostic tests are satisfied.

³ $\Delta_4 gdp_t = \log GDP_t - \log GDP_{t-4} \simeq (GDP_t / GDP_{t-4} - 1)$

Table 1: *Estimated coefficients for the dynamic model (3) (92:Q2 - 01:Q2)*

Coefficient	Estimates	Std.Error	t-value
α	0.009612	0.0020	4.71
ϕ	0.508281	0.1006	5.05
β_1	0.000226	2.66e-05	8.51
β_2	-0.000125	3.28e-05	-3.79
γ	-0.014039	0.0034	-4.08

Following the solution proposed by Santos Silva and Cardoso (2001), we can now apply the Chow-Lin's method for disaggregating the dynamic model (3). In this way, we obtain either an estimate of the unobserved monthly dynamic for GDP and, moreover, we are able to extrapolate for the current period. The high level of correlation between c_t and the disaggregated series (0.93) shows the good quality of the interpolation.

4. Results and conclusion

Table 2 summarizes the main results of this paper in terms of forecasting accuracy. For each quarter, we compare the official figures released by Eurostat with the forecasts obtained by disaggregating Eq.(3). The model has been re-estimated each step taking into account the whole information available at the reference period. The good outcomes can be considered as a valid starting point for further investigation.

Table 2: *Quarterly out-of-sample forecasts of $\Delta_4 gdp_t * 100$*

Quarter	Eurostat	Forecast	Error
00:Q1	3.55	3.41	-0.14
00:Q2	3.81	3.81	0.00
00:Q3	3.21	3.52	0.31
00:Q4	2.83	3.01	0.18
01:Q1	2.37	2.63	0.26
01:Q2	1.65	1.62	-0.03

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