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FINANCIAL AND REAL LATENT FACTORS IN FORECASTING ECONOMIC TIME SERIES

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Abstract: *In this paper we want to assess the impact of real and financial variables in estimating smoothed GDP. We implement the generalized dynamic factor model, on which Eurocoin indicator is based. We assess that the impact of real and financial variables in estimating smoothed GDP, during the structural break in 2008, shows that the role of real data as industrial production, becomes particularly relevant in relation to that concerning financial data as money supply and spread.*

Keywords: *Band-pass filters, Eurocoin approach, real time indicators.*

1. Introduction

Eurocoin is an indicator of the Euro area economic activity concerning the medium to long-run growth (MLRG), published monthly by the Bank of Italy and Centre for Economic Policy Research (CEPR). New Eurocoin (NE) has been recently created [1]. The main aim of this paper is to propose a theoretical framework for implementing Eurocoin methodology by dividing European variables used to build common latent factors, in real and financial variables. We show that a combination between "real MLRG" and "financial MLRG", can be useful to analyze the impact of real and financial variables (e.g. Spread) in short-term forecasting the smoothed GDP (gross domestic product). These procedures are based on the Eurocoin methodology in order to obtain smoothing of a stationary time series, therefore avoiding the occurrence of end-of-sample deterioration. In this work it is analyzed the MLRG that is not precisely the growth-rate cycle or the "business cycle", as in the definition of a cycle even the oscillations of a period longer than eight years are generally removed. In fact, we are interested in the performance of our indicators

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with respect to a measure of the "trend-cycle GDP growth" obtained in the middle of the sample by a band pass bilateral filter on GDP growth components. Removing erratic components can also be done by applying a band pass filter to the GDP growth series ([2],[6]). These filters perform well in the middle of the sample, but they work badly at the beginning and at the end of the sample, since they require knowledge of the future values of GDP, which of course we do not have. This is the main technical reason why it is worthwhile to develop the disaggregated indicators that we will present in detail in the following sections. In Section 2 it is explained the econometric methodology to analyze our data. In Section 3 we also show that the real time performance is a reasonable approach for the examination of estimate accuracy. Real time estimates will be compared to bandpassed Euro Area growth and we assess if the in-sample (ex-post) results are certifiable.

2. The Generalized Dynamic Factor Model in Short Term Forecasting

The generalized dynamic factor model, on which Eurocoin indicator is based, encompasses as a special case the approximate-factor model of Chamberlain and Rothschild [4], that allows for correlated idiosyncratic components but it is static; it generalizes the exact factor model of Sargent and Sims [11] and Geweke [9], which is dynamic but has orthogonal idiosyncratic components. The main theoretical tool in this context is Brillinger's theory of dynamic principal components [3]. In a classic dynamic factor model, considering the scalar time series variable Y_t to forecast and letting X_t be the N-dimensional time series of candidate predictors, it is assumed that (X_t, Y_{t+h}) admits a factor model with r common latent factors F_t:

$$X_t = \Lambda F_t + \varepsilon_t \qquad Y_{t+h} = \beta_F^{'} F_t + \beta_\omega^{'} \omega_t + \varepsilon_{t+h} \tag{1}$$

where ε_t is an $N \times 1$ vector of idiosyncratic disturbances, h is the forecast horizon, $\beta_F^{'}$ and $\beta_\omega^{'}$ are the parameters, ω_t is an $m \times 1$ vector of observed variables (i.e. lags of Y_t) useful, with F_t, to forecast Y_{t+h}. The value of the medium to long run component of the growth c_t, with the coefficients $A_i \left(i = 1,\ldots,m\right)$, at the end of the sample is so estimated: $\hat{c}_T = A_1 F_{1T} + A_2 F_{2T} + \ldots A_m F_{mT}$ where t=T. In this research we develop a new estimation procedure, by using two groups of common factors on which the GDP is projected: R_i and S_i $\left(i = 1,\ldots,m\right)$ will be respectively the common factors relevant to the prediction of "real MLRG" and "financial MLRG", obtained by projecting Euro Area GDP respectively on real and financial variables. The α monthly weights to combine the two smoothed growth indicators will be obtained in real time by the regression method. The dynamic factor model is designed to extract common movements which represent the main sources of variation in the Thomson Financial Datastream (TFD), in order to estimate the smoothed components of European growth. Therefore the latent factors are "smooth factors", which are generalized principal components of current values of the variables in the dataset. Following [8], we use a two-step method, producing firstly an estimate of the spectral density matrix of the unobserved components F_t and ε_t, and then we use this estimate to obtain the factors by means of generalized principal components. We assume that, in our non-parametric approach, the covariance among the disturbances $\varepsilon' s$ is weak, instead of no correlation at all: this is the reason for using "generalized" in the denomination of the model [7]. The methodology that we develop can be summarized in the following way:

$$X_t^S = \hat{\Lambda}_S S_t + \varepsilon_t^S \tag{2}$$

$$X_t^R = \hat{\Lambda}_R R_t + \varepsilon_t^R \tag{3}$$

$$Y_{t+h}^S = \beta_S^{'} S_t + \beta_{\omega S}^{'} \omega_t^S + \varepsilon_{t+h}^S \tag{4}$$

$$Y_{t+h}^R = \beta_R^{'} R_t + \beta_{\omega R}^{'} \omega_t^R + \varepsilon_{t+h}^R \tag{5}$$

where the idiosyncratic disturbances are orthogonal to the factor. It is possible to prove that in a dynamic factor model the principal components of X_t are consistent estimators of the true latent factors [12]. The financial and real variables X_t^S and X_t^R that are used to construct the factors are month-on-month rates of change. Therefore, Y^S is the estimate of the GDP that is obtained only using some financial latent factors; while Y^R is the estimate of the GDP that is obtained by using real latent factors. The medium to long-run growth can be outlined as follows:

$$\hat{c}_T = \alpha_0 + \alpha_1 (A_{1F} S_{1T} + A_{2F} S_{2T} + \ldots. + A_{mS} S_{mT}) + \alpha_2 (A_{1R} R_{1T} + A_{2R} R_{2T} + \ldots.. A_{mR} R_{mT}) \tag{6}$$

3. Comparing real and financial indicators: Real time results

Our model is described by a set of regressors, that are the linear combination of the variables contained in the TFD. The regressors in (2-6) are constructed using techniques from large-dimensional dynamic factor models. We dispose of a dataset consisting of 157 monthly variables (Table 1) during the period between January 1987 and March 2011, and we have developed some programs based on Matlab. In our model X_t is a (157x291) matrix.

The three indicators that we compare in real time to Euro Area bandpassed growth rate are:

- Eurocoin (developed by Bank of Italy and CEPR);
- Financial Eurocoin (that we are developing in this paper, see equation 4 above);
- Real Eurocoin (equation 5 above).

In this section we divide the TFD in real and financial variables. Ex post estimate is looked by analyzing the in-sample 1995-2002; the period 2003-2010 is analyzed in real time with the end of the sample.

Table 1. Variables used in Estimation by Data Source.

Data Source	Variables	Type of data
Surveys	31	Real
Leading Indicators	6	Real
Demand Indicators	12	Real
Industrial Production	32	Real
Wages Indicators	2	Real
Employment Indicators	5	Real
Producer Price Index	26	Real
Exchange rates	3	Real
Imports-Exports	8	Real
Money Supply	8	Financial
STANDARD & POOR'S INDEX	7	Financial
(Italy, Germany, USA, UK) SPREAD	10	Financial
Benchmark Bond	7	Financial
TOTAL	***157***	

According [1], a finite version of the target can be obtained by augmenting y_t^{s} with its sample mean $\hat{\mu}$ in both infinite directions:

$$c_t^{*s} = \beta(L) y_t^{*s}, \text{ where } y_t^{*s} = \begin{cases} y_t & if \quad 1 \le t \le T \\ \hat{\mu} & if \quad t < 1 \;\; or \; t > T \end{cases} \qquad (7)$$

Target value (7), which is not available at the end-of-sample time T, is available with good accuracy only at time T +h, for a suitable h. As a consequence, indicators produced at time T are compared with the target at T produced at time T + h. The performance of the sectoral Eurocoin at time t, with $t \le T - 12$, is measured as the difference between our indicator at time t and the approximate target at t that is obtained using data up to T. Since y_t, the growth rate, is observed only quarterly, we chose an interpolation to calculate the two missing points for each quarter.

3.1 Ability of indicators to approximate the target

In this sub-section we test the capacity of our estimates to approximate the bandpassed target. In 2008-2010 we observe an high variation in GDP volatility.

Table 2. RMSFE among Indicators and European bandpassed GDP.

	1995,6,2002,12 (RMSFE within the sample)	**2003,1,2008,1 (RMSFE in Real Time)**	**2003,1,2010,12 (RMSFE in Real Time)**
Real Eurocoin	**0.12**	**0.13**	**0.44**
Financial Eurocoin	**0.14**	**0.16**	**0.52**
Eurocoin	**0.12**	**0.12**	**0.43**

In Tables 2 and 3 we analyze the performances inside the sample and in real time, where RMSFE is the root mean squared forecast error that is obtained by comparing each of the three indicators to the bandpassed target c_t^{*s}. We observe that performance of Eurocoin Indicator is similar to the one concerning the Real Eurocoin. In Figure 1 we show these three indicators in real time.

Table 3. Correlation among Indicators and European bandpassed GDP.

	1995,6,2002,12 (Within the sample)	2003,1,2008,1 (In Real Time)	2003,1,2010,12 (In Real Time)
Real Eurocoin	**0.91**	**0.87**	**0.88**
Financial Eurocoin	**0.89**	**0.77**	**0.77**
Eurocoin	**0.92**	**0.88**	**0.89**

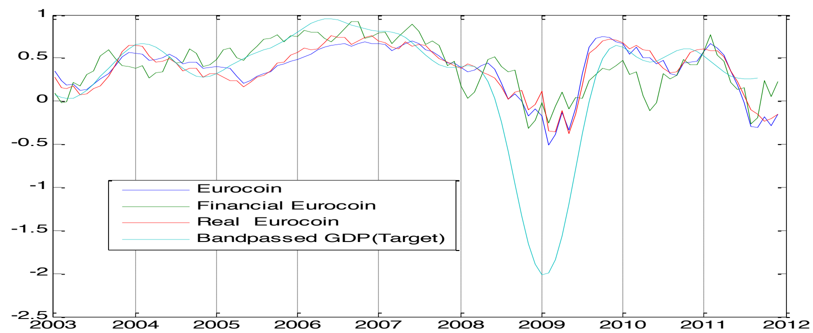

Figure 1. Pseudo Real Time Estimation.

3.2 Ability of real time indicators to signal the correct sign of target change

In this sub-section we investigate the ability to signal the correct change of the bandpassed variation, we use the statistical PT test of [10]. Table 4 shows that PT two sided test is above the 99% critical value for Eurocoin and Real Eurocoin; the Real Eurocoin indicator (the one that is based on real variables) strongly rejects the null hypothesis; for the Financial index we observe a bad performance in terms of prediction of sign.

Table 4. Non-parametric Statistic of Pesaran - Timmermann (PT).

INDICATORS	PT	p-value of the PT test	% Correct prediction of sign of bandpassed Δc^* (2003,1,2010,12)
Eurocoin	2.67	0.01	0.64
Financial Eurocoin	0.15	0.89	0.51
Real Eurocoin	3.89	0.00	0.69

3.3 Ability in signalling turning points in the target

A characteristic of the sectoral indicators that we test in this section, is the ability to give a correct signal of MLRG turning points (TP) in real time (Figure 2). We implement the Bry-Boschan procedure [5]. Since this work is based on fluctuations in quarter on quarter (q-o-q) growth rate, we say that an upturn (downturn) signal in $\hat{c}_t^s$ can be predicting or lagging true upturn, tolerating a four-month error (Table 5). We observe that a dataset of 122 real variables produces results similar to Eurocoin (produced with a dataset of 157 variables) in detecting TP.

Table 5. Real time detection of TP.

Indicators	TP Signals	Correct TP
Bandpassed Target	**5**	**5**
Eurocoin	**5**	**3**
Real Eurocoin	**5**	**3**
Financial Eurocoin	**2**	**2**

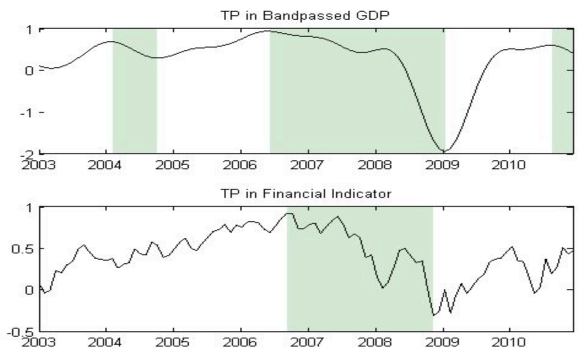

Figure 2. Real time detection of TP.

3.4 Analysis of regression coefficients

We estimate the whole Euro Area MLRG by the following combination of forecasts:

$$c_t = \alpha_t + \beta_{1t} c_t^R + \beta_{2t} c_t^S \tag{8}$$

In (8) the weights α and β are shown updated monthly to underline our regression in real time estimation period (2003-2010) in which c_t indicates bandpassed GDP; c_t^R is the "Real Eurocoin" indicator that we calculate only using real variables; c_t^S is the "Financial Eurocoin" indicator that we calculate using financial variables only. The weights are updated every month on the basis of the newly available information. The values of β_{1t} and β_{2t} are respectively the regression coefficients concerning the Real Eurocoin and Financial Eurocoin. In Figure 3 we show the weights calculated in the combination of real and financial indicators. We observe that the relation between the two coefficients is quite stable till 2008; at the beginning of the last recession, it changes the impact of real and financial data to estimate smoothed GDP.

Figure 3. Combination of real and financial indicators: Regression coefficients.

4. Some Conclusions

In this paper we observe, in particular, that:

- in terms of RMSFE and ability in signalling turning points in the target, the performance of Eurocoin Indicator to approximate the bandpassed target is similar to the one concerning the Real Eurocoin;

- Concerning the Ability of real time indicators to signal the correct sign of target change, the Real Eurocoin indicator (the one that is based on real variables) strongly rejects the null hypothesis that there is no relationship between the direction of change predicted and the observed change; also Eurocoin rejects this hypothesis.
- The Financial indicator produces a good performance in detecting TP only when recession lasts for a long period (about 2-3 years, see Figure 2).

Finally, we can assess that the impact of real and financial variables in estimating smoothed GDP, during the structural break in 2008, shows that the role of real data as industrial production, demand indicators, foreign trade, employment indexes, becomes particularly relevant in relation to that concerning financial data as money supply and spread. One possible explanation could be that interrelations among the recession phase and the variations in production, consumptions and unemployment are highly interrelated.

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