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NOWCASTING ECONOMIC TIME SERIES: REAL VERSUS FINANCIAL COMMON FACTORS

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Abstract:

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

Key words: *Nowcasting; Eurocoin Approach; Medium to' long run component of the growth; Real and Financial Common Factors*

1. INTRODUCTION

Eurocoin, an important application of dynamic factor model, is an indicator of the Euro area economic activity concerning the medium to long-run growth, published monthly by the Bank of Italy and CEPR.

New Eurocoin (NE) has been recently created (Altissimo et al. 2006); it is a timely estimate of the medium to long-run component of euro area GDP (gross domestic product) and it has a measure of performance. NE can be described through the projection of the whole Euro Area bandpassed gross domestic product on a set of regressors – the linear combination of variables contained in the *Thomson Financial Datastream* used by the Bank of

Italy. NE provides an index of the current economic situation in the Euro Area, extracting from the Data Source relevant information which represent the main sources of variation.

We analyze the "medium to long-run component of the growth" (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 8 years are generally removed (Stock and Watson, 1999). In fact, we are interested in the performance of our indicators with respect to a measure of the "trend-cycle growth" in nowcasting (Banbura et al., 2010) smoothed GDP.

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 estimating smoothed GDP. This subdivisions among real economy and financial economy is substantially confirmed in Forni et al. (2003), where they study the impact of financial variables on real data. Our 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.

We build real-time monthly estimates of GDP growth purified from seasonal and other short run fluctuations, as well as from errors in the measurement of GDP, and highly reliable at the end of the sample. In fact, Euro Area GDP is a comprehensive measure of economic activity, but:

1. it is released on a quarterly frequency, with a certain delay and may be subject to significant revisions afterwards;
2. GDP growth may be high or low in any quarter depending on seasonal effects and measurement errors.

Removing erratic components can also be done, for example, by applying a band pass filter to the GDP growth series. This technique, however, presents the same problems in terms of frequency and timeliness, producing some estimates that deteriorate at the end of the sample. Previous research has relied on "two-sided filters" to eliminate seasonal and short-run high frequency noise (Baxter and King, 1999; Christiano and Fitzgerald, 2003).

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 we describe the econometric methodology to analyze our data. In section 3, we show that the *real time performance* is a reasonable approach for the examination of estimate accuracy. Not all observations can be used in estimating parameters. The latter sample will be used to build pseudo estimates by a recursive or a rolling window. We test our models using *pseudo real time estimates* at the end of sample. Real time estimates will be compared to bandpassed Euro Area growth components and we will assess if the in-sample results are certifiable.

2. THE GENERALIZED DYNAMIC FACTOR MODEL

The *generalized dynamic factor model*, on which *Eurocoin* indicator is based, must have two characteristics: it must be dynamic, because business cycle questions are typically non-static. Secondly, it must allow for cross-correlation among idiosyncratic components, as orthogonality is an unrealistic assumption for most applications. An important feature of this model is that the common component is allowed to have an infinite moving average (MA) representation, so as to accommodate for both autoregressive (AR) and MA responses to common factors. Dynamic factor model is more general than a static-factor model in which lagged factors are introduced as additional static factors, since AR responses are ruled out in such a model. This model encompasses as a special case the approximate-factor model of Chamberlain (1983) and Chamberlain and Rothschild (1983), that allows for correlated idiosyncratic components but it is static; it generalizes the *exact* factor model of Sargent and Sims (1977) and Geweke (1977), which is dynamic but has orthogonal idiosyncratic components.

In a classic dynamic factor model (Brillinger, 1981), considering the scalar time series variable Y_t to forecast and let 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:

$$X_t = \Lambda F_t + \varepsilon_t$$

$$Y_{t+h} = \beta_F^{'} F_t + \beta_\omega^{'} \omega_t + \varepsilon_{t+h} \quad (1)$$

where ε_t is an $N \times 1$ vector of idiosyncratic disturbances, h is the forecast horizon, 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}. In the general model, the value of the medium to long run component of the growth c_t, with the coefficients A_i, at the end of the sample is so estimated:

$$\hat{c}_T = A_1 F_{1T} + A_2 F_{2T} + \ldots A_m F_{mT} \quad (2)$$

In this paper, we use two groups of common factors on which the GDP is projected: F_i and R_i (*i* =1, ..., *m*) will be respectively the common factors relevant to the prediction of "real MLRG" and "financial MLRG" (Figure 2), 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 methodology that we develop in this section can be so summarized as in:

$$X_t^F = \Lambda F_t + \varepsilon_t^F \quad (3)$$

$$X_t^R = \Lambda R_t + \varepsilon_t^R \quad (4)$$

$$Y_{t+h}^F = \beta_B^{'} F_t + \beta_\omega^{'} \omega_t^F + \varepsilon_{t+h}^F \quad (5)$$

$$Y_{t+h}^R = \beta_R^{'} R_t + \beta_\omega^{'} \omega_t^R + \varepsilon_{t+h}^R \quad (6)$$

The medium to long-run growth (that we name "Combined Eurocoin") will be equal to:

$$\hat{c}_T =$$
$$\alpha_0 + \alpha_1 (A_{1F} F_{1t} + A_{2F} F_{2t} + ... + A_{mF} F_{mT}) + \alpha_2 (A_{1R} R_{1T} + A_{2R} R_{2T} + ... A_{mR} R_{mT})$$

Or, considering the lags as in (5) and (6), we have:

$$\hat{c}_T = \alpha_0 + \alpha_1 Y^F_{t+h} + \alpha_2 Y^R_{t+h} \quad (7)$$

The comparison between the medium to long-run components, obtained through the traditional method Eurocoin in (2), and the combination specified above in (7), will offer a more specific knowledge with regard to real and financial economic activities.

In the theoretical case of infinite data series, evaluation of the medium to long-run component can easily be done by applying band-pass filtering. In reality, band-pass filter method provides a good approximation in the middle of the sample, while approximations at its ends are very poor, since they require knowledge of the future values of GDP, which of course we do not have. It is not an appropriate approach for real-time analysis. The idea of Eurocoin approach, that we are proposing in this paper, is based on the assumption that a panel of macroeconomic variables capture some information about future GDP dynamics, to perform equally well within and at the end of the sample.

Each real time indicator will be compared to the target that is a band pass bilateral filter on growth rate. Target value, 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, disaggregated indicators produced at time T will be compared with the target at T produced at time T + h.

A finite-sample version of the band-pass filter, equation (8), provides a good approximation to the ideal target at time t in the middle of the sample, and it performs badly at the beginning and end of the sample. Precisely, the performance at time t, with $t \leq T - 12$, will be measured as the difference between our indicator at time t and the approximate target at t that is obtained using data up to T.

According to Altissimo et al. (2006), within a finite sample the following approximation of the target can be obtained, by augmenting $y_t{}^s$ with its sample mean $\hat{\mu}$ in both infinite directions:

$$c_t^{*s} = \beta(L) y_t^{*s}, \text{ where } y_t^{*s} = \begin{cases} y_t & if \quad 1 \leq t \leq T \\ \hat{\mu} & if \quad t < 1 \; or \, t > T \end{cases} \quad (8)$$

Since y_t, the growth rate, is observed only quarterly, while we are interested in a monthly indicator of economic activity, we chose a simple interpolation to calculate the two missing points for each quarter, assuming that y_t is unchanging within a quarter.

It is possible to prove that in a dynamic factor model the principal components (D'Ambra, L., Gallo, M., 2008) of X_t are consistent estimators of the true latent factors.

3. COMBINING REAL AND FINANCIAL VARIABLES: REAL TIME RESULTS

Nowcasting GDP requires to focus on times series data that can provide information on the current state of the economy. There are numerous macroeconomic time series with shorter publication delays than GDP. This is mostly the case for monthly statistics related to employment, industrial production, financial variables or business surveys published by Central Banks or National Statistics Institutes.

At this stage, two main approaches exist in econometric literature to choose the variables useful for the nowcast of growth rate; the first focus on a limited number of series and it consists in selecting a reduced number of variables and tracking their development. The selection criteria are generally based on:

- the ex-post ability of the series to reproduce reference time series movements;
- a priori belief based on economic theory;
- the choice can almost be judged as subjective.

The series can either be individually tracked or aggregated in a synthetic index. The former is a strategy that has been adopted by the Conference Board and the OECD. Since in the present paper we implement Eurocoin indicator, we will be using generalized dynamic factor model (on which Eurocoin is based) to construct some monthly indicators of economic activities in Euro Area, and we assume two different representations for the economic development: the first can be obtained by considering a large dataset of real European variables; the second will consider a smaller dataset of international financial variables. We dispose of a dataset consisting of 157 monthly macroeconomic variables during the period between January 1987 and March 2011. The main blocks of macroeconomic indicators are as follows (table 1):

- Business and consumer confidence indicators – the largest block;
- Industrial production indices;
- OECD Composite Leading Indicator;
- Producer price index for: intermediate and capital goods; energy, industry, investment and intermediate goods; durable and non durable goods;
- Retail Sales;
- Variables describing external transactions: exports and imports of goods and services.
- Financial data: monetary variables, interest rates, effective exchange rates.

Table 1. *Variables used in Estimation by Data Source*

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

We focus on medium to long-run components of the growth (MLRG), i.e. the smoothed components of GDP growth rate obtained by removing the fluctuations of period shorter than or equal to one year, and it bears no relationship to any definition of trend. Monthly indicators are commonly used in the prediction of current data on GDP before the data are available. For the Euro area, a flash estimate of GDP is released by Eurostat about six weeks after the end of the reference quarter, and a full set of indicators for the second quarter of the year is not available any earlier than the GDP flash estimate. Also in this section we divide the 157 variables contained in Thomson Financial Datastream in real and financial variables. In (7), we have shown a combination (using regression method to determine the relative weights) of real and financial MLRG; in the *Combined Eurocoin* the regression method is used to determine the relative weights: this combination is useful to analyze the impact of real and financial data in estimating smoothed GDP, that is the main aim of this paper.

Ex post estimate is looked at in this section by analyzing the in-sample 1995-2002; the period 2003-2010 will be analyzed in real time with the end of the sample. Experiments conducted in this paper use 5 generalized principal components, the number estimated over the whole sample period [1 T]. The exercises we develop use the estimates $\hat{c}_t(t+h)$, of each disaggregated indicators at time t using the data from 1 to t + h, h = 0, 1, 2, with t running from January 2003 to December 2010.

Real time estimations are built from 2003 to 2008 and from 2003 to 2010 separately, as in 2008-2010 we observe a strong recession and an high variation in GDP volatility. Analysis of real time performance, in this section will regard:

- ability of real time indicators to approximate the target. It will be measured as the difference between our indicator at time t and the approximate target at t that is obtained using data up to T, by calculating the RMSFE (root mean squared forecast error). Real time error include both uncertainty concerning future values of error term and that arising due to the fact that regression coefficients are estimated (see sub-section 3.1);
- ability of real time indicators to signal the correct sign of target change and in signalling turning points (sub-section 3.2);
- analysis of regression coefficients in equation (7) above described (sub-section 3.3).

Our experiment is useful in the analysis of the impact of real data on estimate smoothed GDP in the different business cycle phases. So, we have outlined two data groups: a first containing "*real economic activity variables*"and a second with "*financial variables*". In our experiments the approximate target is the bandpassed Euro Area growth rate, the same that is generally used to test the performance of the Eurocoin indicator. In the following, the following indicators are compared:

- Eurocoin;
- Financial Eurocoin;
- Real Eurocoin.

3.1 Ability of indicators to approximate the target

Real Time performance is computed by using the following steps and it gives a sense of how well the model has gone at the end of the sample (Figure 1):

1. Select a date near the end of the sample;
2. Estimate model using data up to that date;

3. Use estimated model to produce some forecasts/estimates, by using a recursive window as follows: the initial estimation date is fixed, but additional information is added one at a time to the estimation period.

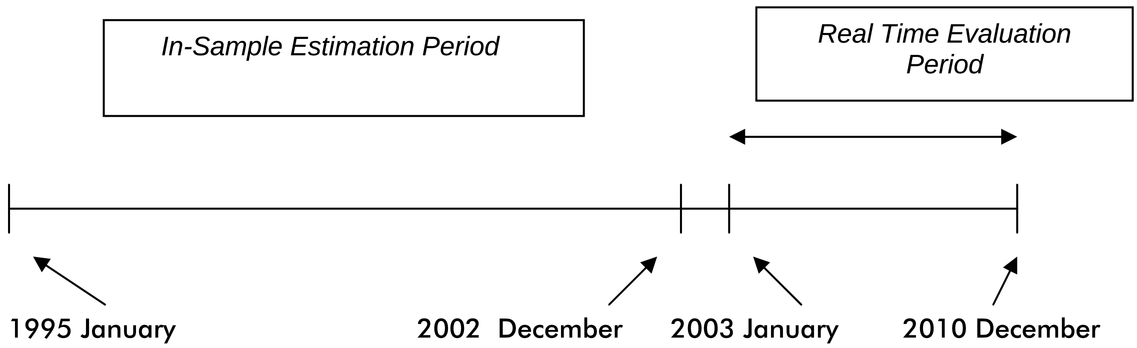


Figure 1. *Use of In Sample and an Real Time Estimation in our research*

In this sub-section we test the capacity of our estimates inside the sample and in real time to approximate the bandpassed target.

Table 2. *RMSFE among Indicators and European bandpassed GDP*

Indicators	1995-2002 (Rmse within the sample)	2003-2008 (Rmse in Real Time)	2003-2010 (Rmse in Real Time)
Real Eurocoin	0.12	0.129	0.44
Financial Eurocoin	0.14	0.161	0.52
Eurocoin	0.12	0.125	0.43

In table 2 and 3 we analyze the performances inside the sample and in real time, since June 1995 to December 2010. We observe, in particular, that performance of Eurocoin Indicator is strongly similar to the one concerning the Real Eurocoin. Our elaboration are based on Thomson Financial Datastream.

Table 3. *Correlation among Indicators and European bandpassed GDP*

Indicators	1995-2002 (Within the sample)	2003-2008 (In Real Time)	2003-2010 (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

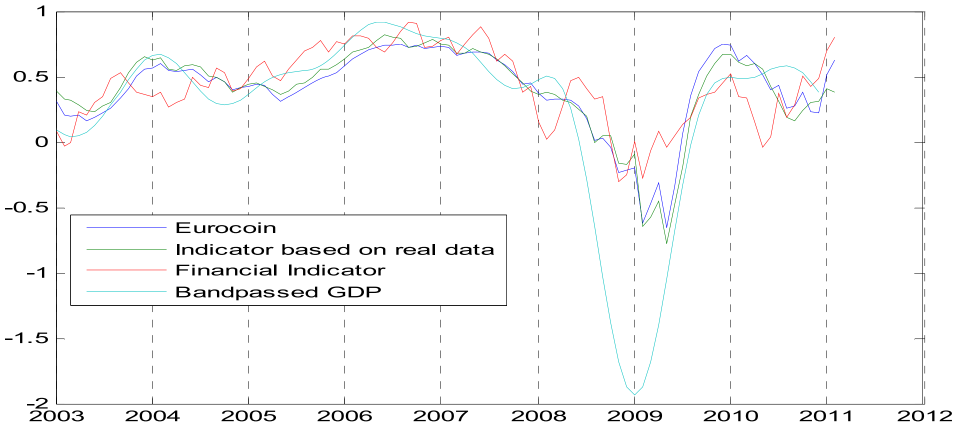


Figure 2. *Pseudo Real Time Estimation*

3.2. Ability to signal the correct sign of target change and turning points

In this sub-section we investigate the capacity of real time indicators to signal the correct sign of target change. To assess the ability of $\Delta \hat{c}_t^s(t)$ to signal the correct change of the bandpassed variation $\Delta c_t^{*s}(T)$, we use the statistical test of Pesaran and Timmermann (1992). In synthesis, Pesaran and Timmermann proposed a directional accuracy (DA) test of the hypothesis that there is no relationship between the direction of change predicted by a model and the observed change. Concerning our disaggregated estimates, if P is the proportion of times the sign of the bandpassed Euro Area growth rate (the approximate target) that is correctly predicted by the three indicators in real time, and P_star is the probability of the correct sign being estimated under the assumption that the predictor is independent from the predicted variable, we can shortly highlight, following Pesaran and Timmermann (1992), that

$$S\_n = \frac{(P - P\_star)}{\sqrt{Var(P) - Var(P\_star)}}$$

is approximately normal.

We observe that:

- PT two sided test is above the 99% critical value forEurocoin and Real Eurocoin
- the Real Eurocoin indicator (the one that is based on real variables) strongly rejects the null hypothesis;
- for the Financial indicator we observe a bad performance in terms of correct prediction of sign.

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

Indicators	PT	p-value of the PT test statistic	% Correct prediction of sign of bandpassed Δc*2003-2009
Eurocoin	2.67	0.0075	0.64
Financial Eurocoin	0.15	0.8837	0.51
Real Eurocoin	3.89	0.000	0.69

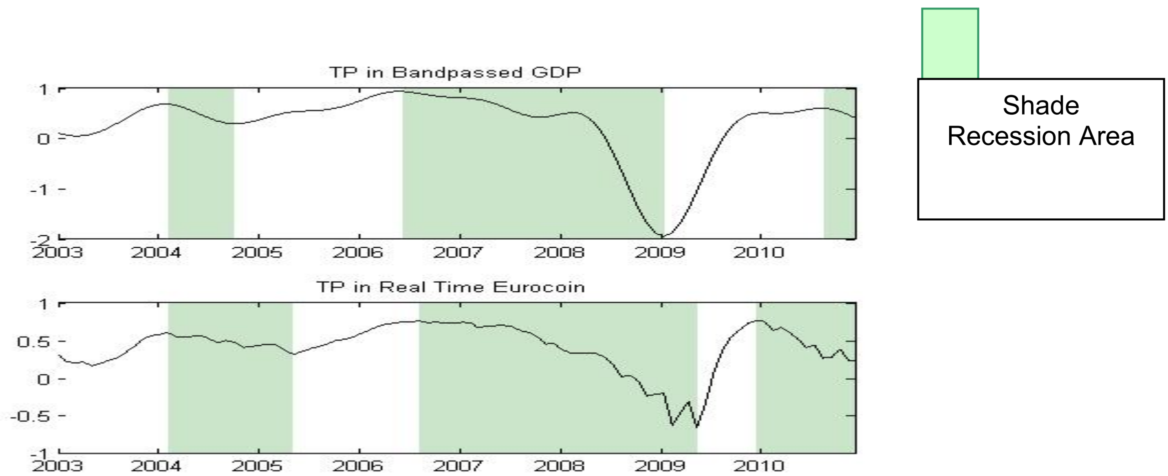
A characteristic of the indicators that we test in this chapter, is the ability to give a correct signal of MLRG turning points in real time. In the simplified *Bry-Boschan* procedure (1971), used in the OECD CLI system for turning point identification, these censor rules guarantee the alternation of peaks and troughs, while ensuring that phases last not less than 9 months and cycles last not less than 2 years". This methodology is based on the concept which focuses on fluctuations in the absolute level of economic activity; however, since this work is based on fluctuations in 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. *Number of Turning Points in the Bandpassed Target*

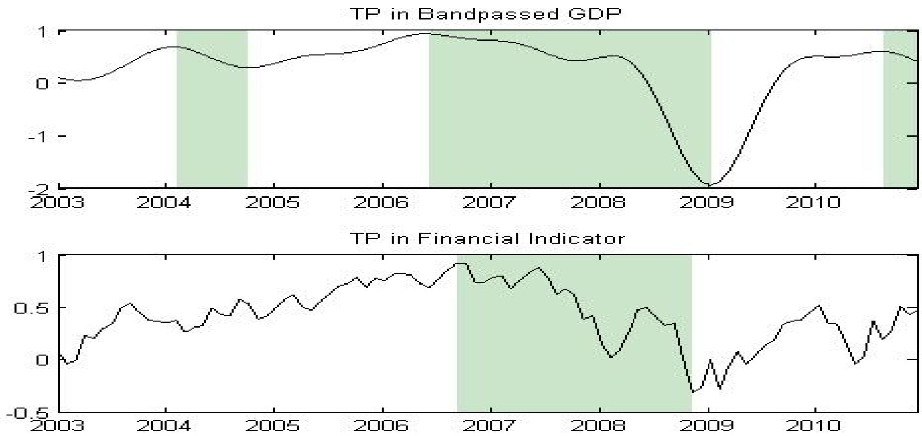
TOTAL TURNING POINTS	DOWNTURNS	UPTURNS
5	3	2

Table 6. *Real time detection of turning points (TP)*

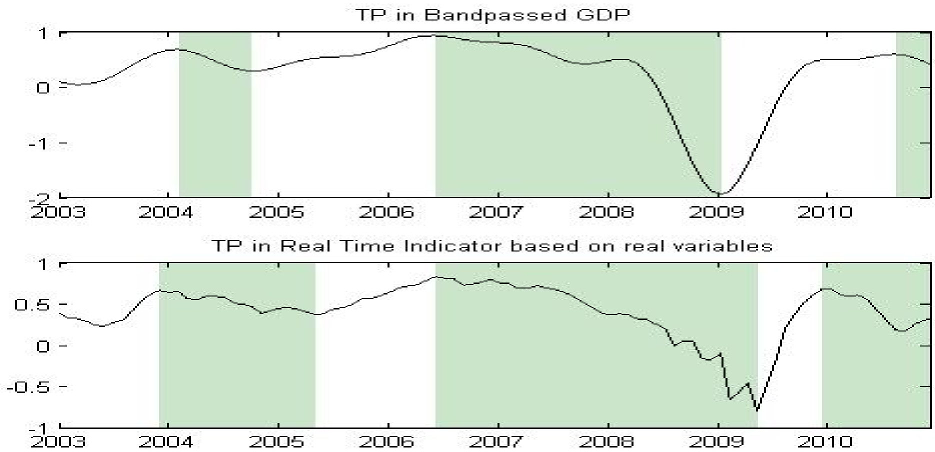
SECTORS	TP Signals	Correct TP	Correct over signalled TP	Missed over all TP
Eurocoin	5	3	3/5	2/5
Indicator based on real variables	5	3	3/5	2/5
Financial Indicator	2	2	2/5	3/5



a) Bandpassed Target versus Eurocoin



b) Bandpassed Target versus Financial Eurocoin



c) Bandpassed Target versus Real Eurocoin

Figure 3. Real Time detection of Turning points

Therefore, we observe that a large dataset of 122 *real variables*, in terms of TP, produces some results similar to Eurocoin (produced with a dataset of 157 variables) in detecting TP in bandpassed target. Differently, a real time indicator based on *financial variables*, and based on a small dataset (35 variables), produces a satisfactory performance in detecting TP when recession lasts for a long period (in our exercise concerning Euro Area, it concerns the 2003 – 2009).

3.3. Forecasting the crisis by the regression coefficients

In the equation (9) the weights α and β are shown updated monthly to underline our regression in real time estimation period (2003-2010)

$$c_t = \alpha_t + \beta_{1t} c_t^R + \beta_{2t} c_t^F \qquad (9)$$

in which c_t indicates bandpassed GDP; c_t^R is the "Real Eurocoin" indicator that we calculate only using real variables; c_t^F 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. In Figure 4 that follows we show the weights (regression coefficients) calculated in the combination of real and financial indicator: the Combined Eurocoin is calculated by following the equations (7) and (9). In Figure 4, we observe that the relation between the two coefficients is quite stable till 2008; at the beginning of the last recession (during 2008), it changes the impact of real and financial data to estimate smoothed GDP, and in 2009 (at the trough) the distance becomes the minimum; during 2009, when recovery begins, it is shown that the impact of real data to estimate GDP becomes more important than the one concerning financial data. This matter could help the econometrician to forecast economic crisis.

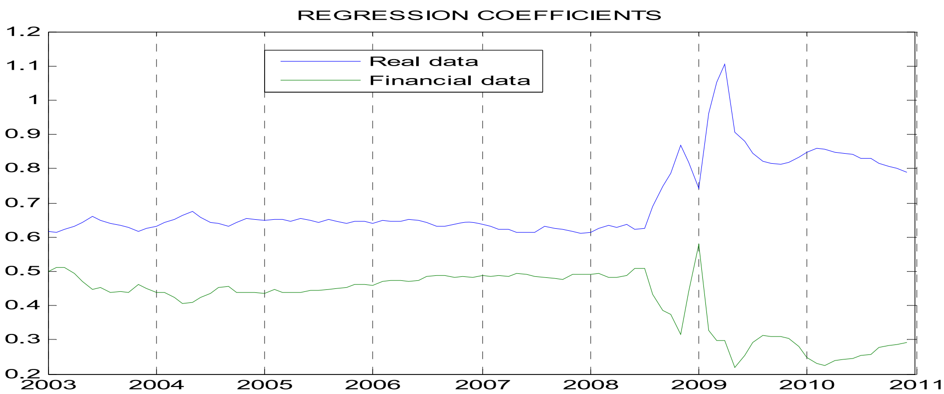


Figure 4. Regression coefficients

4. FINAL REMARKS

In this work we analyze the behaviour concerning a combination of generalized dynamic factor models, compared to a classic Eurocoin indicator (that is produced by using the whole dataset of real and financial variables).

We observe, in particular, that:

- in terms of RMSE and correlation, the performance of Eurocoin Indicator to approximate the bandpassed target is very similar to the one concerning the Real Eurocoin; also concerning the ability in signalling turning points in the target, their performances are quite similar.
- 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*, that is based on a small dataset (35 variables), produces a good performance in detecting TP only when recession lasts for a long period.

Finally, we can assess (Figure 4) 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 (Import, Export), Employment Indexes, becomes particularly relevant in relation to that concerning financial data as Exchange rates, Money Supply, Spreads. So, one possible explanation could be that interrelations among the recession phase and the variations in production, consumptions and unemployment are highly interrelated.
Concerning further developments of our research, it could be useful to use a larger dataset of historical series.

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