Advances in econometric tools to complement official statistics in the field of Principal European Economic Indicators

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Abstract

The paper presents ongoing activity carried out at Eurostat in the field of Principal European Economic Indicators (PEEIs) on econometric tools for increasing their relevance of short term statistics. Three lines of methodologies are here presented: the first is aimed to increase data timeliness and concerns the framework for nowcasting and density forecast as well as that on coincident indicators. Nowcasting implies a general linear regression as reference model, whereas coincident indicators are based on bridge- and factor-models complemented by intensive application of the LARS algorithm. The second line of research concerns the construction of high frequency indicators of economic activity mainly based on state space models applied to data available at mixed frequency. We present Euro-MIND, the monthly coincident indicator for the euro area, and all its most recent extensions. The last part provides the recent efforts towards the system of coincident turning point indicators for the business cycle, growth cycle and acceleration cycle, through univariate and multivariate Markov-Switching models. We discuss methods and applications to data concerning the euro area. We conclude that all these instruments efficiently complement traditional official statistics in the desired direction, providing a powerful framework for data analysis and diagnosis.

Keywords: short term statistics, nowcasting, regression methods, LARS algorithm, state space models, Markow-Switching models

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1. Introduction

Principal European Economic Indicators (PEEIs) constitute the core of infra-annual macroeconomics statistics. They have been set-up in 2002 by the Commission Communication COM/2002/661 which also included a development plan to increase their timeliness and coverage. Despite the sensible progress achieved since then, PEEIs still present some gaps, when compared to the corresponding US indicators, and they do not completely fulfil user's needs especially in terms of timeliness, length, high frequency availability and ability to display clearly cyclical signals. Achieving such objectives within the official statistical context can take several years and some of such requirements, such as the ability of displaying cyclical signals, are not directly linked to the improvement of the data production process. PEEIs remain an essential set of indicators for short term monitoring and analysis as demonstrated by the release of the PEEIs page in 2007 and by the fact that PEEIs have been considered as the starting point for the development of wider set of indicators such as PGIs and the data template proposed by the UNSD. Complementing PEEIs with advanced econometric tools can contribute to better meet user needs in all areas mentioned before.

This paper presents some econometric tools recently investigated by Eurostat in the field of PEEIs to increase the timeliness of official statistics, their availability at higher frequency as well as the readability of cyclical signals. Three lines of methodologies are here presented: the first is aimed to increase data timeliness and concerns the framework for nowcasting and density forecast as well as that on coincident indicators. Nowcasting implies a general linear regression as reference model, whereas coincident indicators are based on bridge- and factor-models complemented by intensive application of the LARS algorithm. The second line of research concerns the construction of high frequency indicators of economic activity mainly based on state space models applied to data available at mixed frequency. We present Euro-MIND, the monthly coincident indicator for the euro area, and all its most recent extensions. The last part provides the recent efforts towards the system of coincident turning point indicators for the business cycle, growth cycle and acceleration cycle, through univariate and multivariate Markov-Switching models. We discuss methods and applications to data concerning the euro area.

The paper is structured as follows: section 2 presents alternative ways to increase timeliness, section 3 presents a way forward to develop a set of monthly indicators originally available at quarterly level, while section 4 describes a system for extracting cyclical signals and, in particular, turning points. Finally, section 5 shortly concludes.

2. Nowcasting techniques in use at Eurostat

The use of statistical and econometric techniques can significantly contribute to the increase of timeliness in the short and medium term. In this context, a key tool is represented by a set of forecasting techniques adapted to estimate the recent past or the present as well as the near future.

The nowcasts, which we are working on, are based on the following main principles agreed inside Eurostat:

whenever partial information on the target variable, either at geographic or sectoral level, is available, this has to be included in the flash estimation model;

soft data (e.g. business and consumer surveys) can be integrated into the model under the condition that a minimum amount of hard data is available;

in order to increase forecasting accuracy, statistically related indicators (e.g. conventional earnings in case of nowcasts of Labour Cost Index) can be used in the model either in case of unavailability of significant partial information on the target variable or to complement such partial information;

any hypothesis based on economic theories has to be avoided in the model specifications;

purely univariate models should not be taken into account but only used as a benchmark in the simulation exercise;

the selected model should be as simple as possible, statistically sound, easy to use in the regular production process and characterized by a very simple dynamic specification where whenever needed.

The framework in use at Eurostat is based on the following general regression equation:

$$\Delta y_t = c + \sum_{i=1}^{p} \alpha_i \Delta y_{t-i} + \sum_{i=0}^{p} \sum_{j=1}^{k} \beta_{ij} x_{t-i,j} + u_t, \quad t = 1,\dots,T \qquad (1)$$

where y_t is the log of the dependent variable, $x_{t,j}$ is the j-th indicator variable (j = 1, 2, ..., k) in logs when appropriate, c is an intercept, p is the number of lags, Δ is the first-difference operator and u_t is a mean zero disturbance with variance σ^2. All indicator variables that enter (1), if necessary, are differenced until stationary. The use of (log) first differences, except for series (like the survey balances) which by definition are bounded and hence I(0), is deemed sufficient to render all series stationary. Cointegrating restrictions are imposed when cointegration is present.

It should be noted that contemporaneous values of the indicator variables are included in (1). This reflects the fact that these indicators by their nature are published ahead of the variables to which they are assumed to relate, even though they may relate to the same time period.

The modelling framework requires only a one period ahead forecast. This means that there is no distinction between single equation and multivariate models such as VAR models. Furthermore, for short horizons the forecasting performance from univariate nonlinear models is typically worse or not much better. We therefore confine attention to simpler linear models.

The general model of equation (1) involves considering a reasonably large set of possible indicators, among which national as well as Euro indicator variables, their lags, and then estimating a large number of models. Given k indicator variables (our review of data suggests that k is unlikely to exceed 4) and a given number of lags (we consider p = 2), for t = *1, ..., T*, we consider all possible combinations of (1) of the twelve exogenous and two lagged endogenous variables thus generated. Since, however, this creates a very large possible number of regressions and bearing in mind the well-known benefits of parsimony in forecasting models, we limit ourselves to those equations containing no more than four explanatory variables. There are in total 1470 such equations.

We then “automatically” select the preferred model using the Bayesian Information Criterion (BIC). Use this model, and its estimated coefficients, and the time *T* values of the explanatory variables in the preferred FLASH model for time *T*. This provides the model we use to forecast for period *T + 1*. In order to provide some stability to the forecasting process, we will review model selection annually.

Efficiency tests of unbiasedness and efficiency for the nowcasts are carried out using the following regression equation:

$$y_t - \hat{y}_t = \alpha^{\varepsilon} + \beta^{\varepsilon} f_{t-1} + \varepsilon_t \qquad (2)$$

where y_t is the outturn (whether measured by the first, second or final release), $\hat{y}_t$ is the nowcast and f_{t-1} is information known at the time the nowcast is made.

Unbiasedness and efficiency therefore require that the forecast error $y_t - \hat{y}_t$ is mean zero and uncorrelated with this known (lagged) information, implying $\alpha^{\varepsilon} = \beta^{\varepsilon} = 0$. We simply set $f_{t-1} = \hat{y}_t$ so that our tests are ones of whether the nowcasts and their errors are uncorrelated. If there is a relationship, the nowcasts are inefficient and could be improved.

To provide an indication of the likely revision associated with the nowcasts produced in real-time we follow Planas & Rossi (2004) by building up an empirical estimate of the likely revision. Put simply, to quantify the uncertainty of the nowcast $\hat{y}_t$ we produce 95% intervals based on

$$\hat{y}_t \pm 1.96 r_t \qquad (3)$$

where r_t is such that

$$r_t = \frac{1}{p-1}\sum_{i=1}^{p}\left(y_{t-i} - \hat{y}_{t-i}\right)^2 \qquad (4)$$

is the RMSE of nowcasts made at time (t − 1) and earlier (back to (t − p)), with the RMSE calculated against the outturn (first or final). p is determined by the length of the sample of nowcasts available.

2.1 Application to PEEIs

The Eurostat now-casting strategy presented so far is applied since 2006 to a set of short term statistics for the euro area. In what follows we show the results for GDP and the Producer Price Index (PPI hereafter). In particular, Tables 1 and 2 provide the detail of flash estimates at t+15 days, our now-cast estimates, in comparison with the first and the final official estimates released by Eurostat; errors of now-casts with respect to the two official releases are also shown.

Table 1 shows for the period Q4 2008 – Q3 2010 the real time simulation of the flash estimates for the GDP against the Eurostat first and final estimates for the euro area.

Table 1: Euro Area Flash Estimates of GDP Growth

	Flash t+15 days	Eurostat First estimate	Eurostat Final estimate	Error First estimate	Error Final estimate
2008q04	-0.94	-1.59	-1.86	-0.64	-0.91
2009q01	-1.55	-2.56	-2.01	-1.01	-0.47
2009q02	-1.13	-0.18	-0.15	0.96	0.99
2009q03	0.68	0.42	0.43	-0.26	-0.25
2009q04	0.74	0.04	0.20	-0.70	-0.54
2010q01	1.18	0.20	0.34	-0.97	-0.84
2010q02	0.83	0.95	0.95	0.12	0.12
2010q03	0.66	0.34	0.39	-0.32	-0.27
2010q04	0.67	0.28	0.26	-0.39	-0.41
2011q01	0.86	0.95	0.80	0.09	-0.06
2011q02	0.62	0.20	-	-0.42	-

Source: Authors' calculations

For GDP the preferred model uses two months of within quarter IP data and the latest quarter's value of the Economic Sentiment Indicator ("soft" survey data, published by DG ECFIN).

There are no sign discordances between flash estimates relative to the modelling strategy and the Eurostat official releases; however the comparison shows some significant errors like the under-estimation during the recession phases (i.e. 2009q02) and the over-estimation in the expansive phase (i.e. 2009q04 and 2010q01). Probably the model, though correct, needs some improvements.

Concerning the under-estimation and both the over-estimations of the first and second quarter of 2009, it can be explained by the procedures of outliers correction within the Seasonal Adjustment methods used by the Member States, which are difficult to be incorporated into the nowcasting exercise. Finally, it has to be noted that the current practise to derive euro area seasonally adjusted data for GDP with summing up national seasonally adjusted data makes difficult the direct construction of a nowcasting model for the euro area as a whole.

The table 2 shows for the period April 2007 – August 2010 the real time simulation of the flash estimates for the Producer Price Index against the Eurostat first and final estimates for the euro area. The selected model is based on German industrial output price and energy prices data according to the BIC selection criterion. Results appear quite encouraging: despite the presence of two cases of sign discordance, often the flash is quite close to Eurostat first estimates. The regression model reacts quite well to the change of regime even if a bit slowly. The variables have been selected among a large set of potential variables. Our opinion is that this constitutes a very good starting point, which could be easily improved either by adding more national information either by including euro area Import Prices which were not yet available when we started the simulation.

2.2 Density nowcasts

The traditional approach to nowcast of previous section focuses on the "point" estimate, which suffers for the lack of indication of the degree of uncertainty associated with the nowcasts. Consequently, to provide a complete description of the uncertainty associated with the point nowcasts there is the need to go towards the concept of *density* nowcasts.

A density nowcast provides an estimate of the probability distribution of its possible future values.

The approach followed by Eurostat is focused on single component models which take the simple form of the regression equation (1). We estimate a set of linear regressions of the target variable (in growth rates) on a single indicator variable. In the variable selection we distinguish between quantitative ("hard") and qualitative ("soft") indicator variables, the latter typically published ahead of hard data. See Giannone et al. (2008) at this purpose. Then we combine the component density nowcasts using the linear pool approach developed by Timmerman (2006).

Most of the applications refer to the case in which the target is a quarterly variable and the indicator is monthly. In this case the indicator is released three times a quarter and, following Kitchen and Monaco (2003), we estimate three component models for each indicator following:

$$\Delta y_t = \beta_0 + \beta_1 x^m_{k,t} + e_t \qquad (5)$$

where Δy_t is the target variable, e_t is the error term assumed to be normally distributed, $x^m_{k,t}$ is the k-th indicator variable from the information set Ω^j_t; m = 1,2,3 denotes the month in the quarter t, (t = 1, ..., T); j = 1, ..., J denotes the first, ..., J-th nowcast formed at different lags from time t. Each successive nowcast exploits an ever larger information set. This reflects the fact that with the passage of time more and more indicator data become available.

The quarterly transformation of the monthly survey data involves transforming $x^m_{k,t}$ in a manner consistent with the quarterly variable Δy_t (which represents quarterly growth at a quarterly rate). This is achieved, for example, following Mariano & Murasawa (2003).

Table 2: Euro Area Flash Estimates of Producer Price Index

	Flash t+16	Eurostat First estimate	Eurostat Final estimate	Error First estimate	Error Final estimate
2007m4	0.31	0.45	0.42	0.14	0.11
2007m5	0.28	0.29	0.43	0.01	0.15
2007m6	0.31	0.13	0.12	-0.18	-0.19
2007m7	0.25	0.26	0.29	0.01	0.04
2007m8	0.31	0.06	0.15	-0.25	-0.16
2007m9	0.24	0.36	0.41	0.12	0.17
2007m10	0.33	0.64	0.67	0.31	0.34
2007m11	0.78	0.90	0.92	0.12	0.14
2007m12	0.11	0.10	0.19	-0.01	0.08
2008m01	0.43	0.85	0.78	0.42	0.35
2008m02	0.74	0.66	0.61	-0.08	-0.13
2008m03	0.65	0.70	0.66	0.05	0.01
2008m04	0.97	0.79	0.77	-0.18	-0.20
2008m05	0.93	1.21	1.16	0.28	0.23
2008m06	0.90	0.96	1.06	0.06	0.16
2008m07	1.73	1.23	1.33	-0.50	-0.40
2008m08	-0.25	-0.50	-0.51	-0.25	-0.26
2008m09	0.23	-0.20	-0.18	-0.43	-0.41
2008m10	0.01	-0.80	-0.87	-0.81	-0.88
2008m11	-1.26	-1.96	-2.14	-0.70	-0.88
2008m12	-1.19	-1.58	-1.54	-0.39	-0.35
2009m01	-0.79	-0.88	-1.22	-0.09	-0.43
2009m02	-0.57	-0.43	-0.49	0.14	0.08
2009m03	-0.69	-0.71	-0.69	-0.02	0.00
2009m04	-1.25	-1.06	-0.87	0.18	0.38
2009m05	-0.18	-0.17	-0.05	0.01	0.13
2009m06	-0.09	0.31	0.42	0.40	0.50
2009m07	-1.16	-0.77	-0.69	0.38	0.46
2009m08	-0.32	0.48	0.51	0.80	0.83
2009m09	-0.27	-0.36	-0.35	-0.09	-0.08
2009m10	0.04	0.27	0.29	0.23	0.25
2009m11	0.11	0.18	0.17	0.07	0.06
2009m12	0.09	0.10	0.06	0.01	-0.03
2010m01	0.65	0.66	0.73	0.01	0.07
2010m02	0.10	0.13	0.13	0.03	0.03
2010m03	0.56	0.61	0.59	0.05	0.03
2010m04	0.80	0.93	0.98	0.13	0.17
2010m05	0.43	0.30	0.28	-0.13	-0.15
2010m06	0.59	0.30	0.34	-0.29	-0.25
2010m07	0.51	0.26	0.21	-0.25	-0.30
2010m08	0.08	0.11	0.11	0.03	0.03

Source: Authors' calculations

We then combined the density by the linear opinion pool approach, Timmerman (2006). Given i = 1,..., Nj component models, the combination densities for Δy_τ growth are given by the linear opinion pool:

$$p(\Delta y_\tau) = \sum_i w_{i,\tau,j}\, g(\Delta y_\tau \mid \Omega^j_\tau) \qquad (6)$$

where $g(\Delta y_\tau \mid \Omega^j_\tau)$ are the nowcast densities from component model i, i = 1,..., Nj of Δy_τ conditional on the information set Ω^j_τ.

These densities are obtained having estimated the (5).

The non-negative weights, $w_{i,\tau,j}$, which sum to unity, are constructed in two ways: equal weights (EW) strategy and the Recursive Weight (RW) strategy. The EW strategy attaches equal (prior) weight to each model with no updating of the weights through the recursive analysis:

$$w_{i,\tau\, j} = w_{i,j} = 1/N_j \qquad (7)$$

Secondly, we construct the weights $w_{i,\tau,j}$ based on the fit of the individual model forecast densities: the Recursive Weight (RW) strategy. Following Jore et al. (2010) and Garratt, Mitchell & Vahey (2009), we use the logarithmic score to measure density fit for each model through the evaluation period. The logarithmic scoring rule is intuitively appealing as it gives a high score to a density forecast that assigns a high probability to the realised value. The recursive weights for the nowcast densities take the form:

$$w_{i,\tau,j} = \frac{\exp\left[\sum_{\underline{\tau}-8}^{\tau-1} \ln g(\Delta y_\tau \mid \Omega^j_\tau)\right]}{\sum_{i=1}^{N} \exp\left[\sum_{\underline{\tau}-8}^{\tau-1} \ln g(\Delta y_\tau \mid \Omega^j_\tau)\right]}, \qquad \tau = \underline{\tau}, \ldots, \overline{\tau} \quad (8)$$

In constructing the combined densities using the linear opinion pool, we evaluate the density forecasts using the logarithmic score at each recursion. We emphasise that in deriving the weights based on this measure of density fit, the component models are repeatedly evaluated using real-time data. These weights provide an indication of whether the support for the component models is similar, or not, based on the score of the individual densities. A finding of similar weights across component models would be consistent with the equal-weight strategy.

The next step is the evaluation of nowcast density combination. A popular method, following Rosenblatt (1952), Dawid (1984) and Diebold et al. (1998), is to use the probability integral transforms (pits) z_t of the realization of the variable with respect to forecast density:

$$z_\tau = \int_{-\infty}^{\Delta y \tau} p(u)du \qquad (9)$$

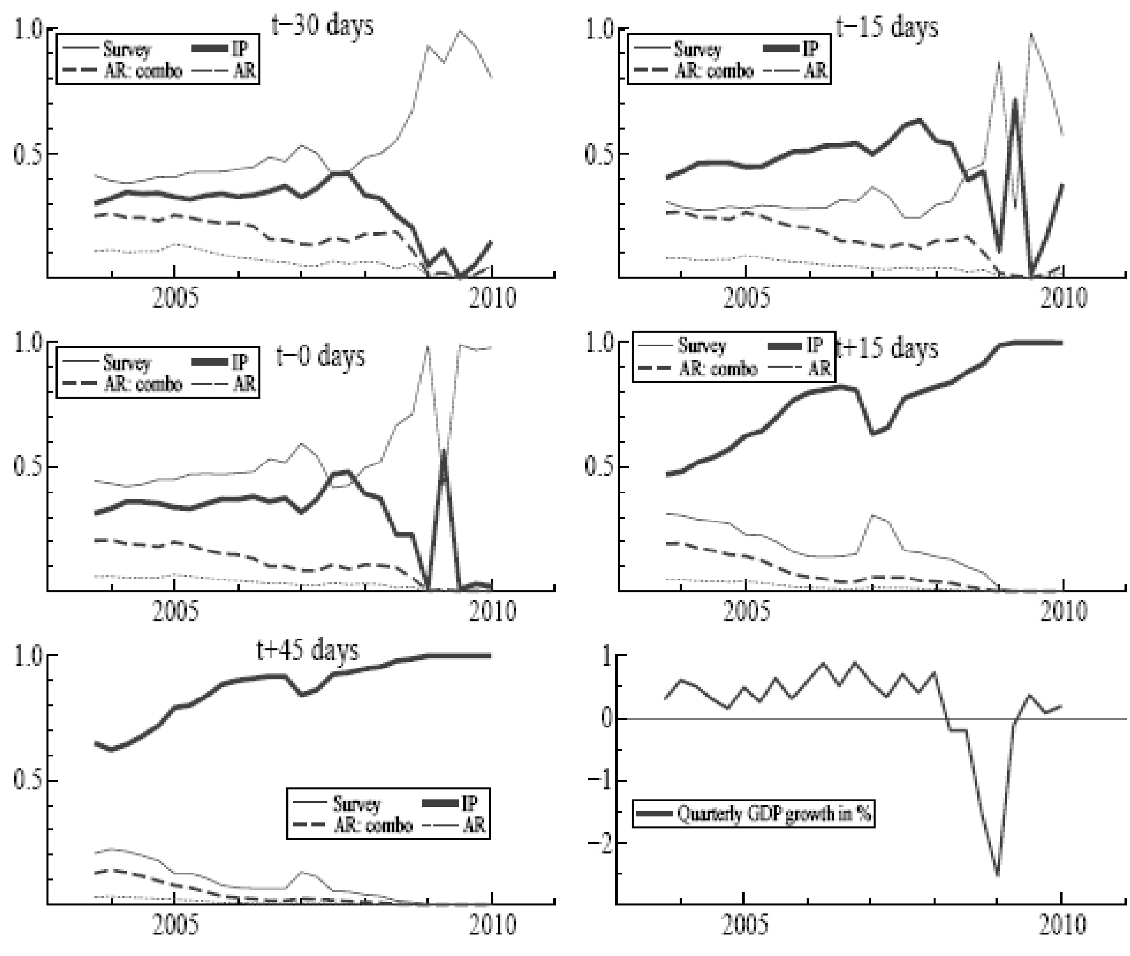
and the application of tests for goodness of fit as Likelihood Ratio (LR), as proposed by Berkowitz (2001), Anderson-Darling (AD) for uniformity of the pits(a modification of Kolmogorov-Smirnov) and Ljung-Box (LB) for independence of the pits. Pearson Chi-squared, following Wallis (2003), are also used to test the uniformity of resulting pits histogram.

2.2.1 THE EMPIRICAL APPLICATION

We compare the accuracy of nowcasts of Euro-area GDP growth at the five horizons (j = 1, .., 5) in recursive out-of-sample experiments using real-time data. Specifically, we use the real-time data for real GDP and industrial production available from Eurostat. Nowcasts for GDP growth are computed recursively from 2003q2-2010q1 using the density forecast combination approach at j = 1, ..., 5; i.e., t-30, t-15, t+0, t+15 and t+45 days. We break our results into two parts: the RW weights on the soft indicators, the hard indicators and lagged GDP growth derived from the logarithmic score of the component forecast densities; and, the evaluations of the recursive weight, RW, and equal weight, EW, strategies for combination.

Figure 1 presents the recursive weights on the soft indicators (i.e., survey data and interest rate spread), hard indicators (i.e. IP) and lagged values of GDP growth for the five nowcast horizons, j = 1, ..., 5.

Figure 1: **Recursive weights on soft and hard indicators and lagged values of GDP growth for 5 nowcast horizons**



Source: Authors' calculations

The figure 1 shows interesting results:

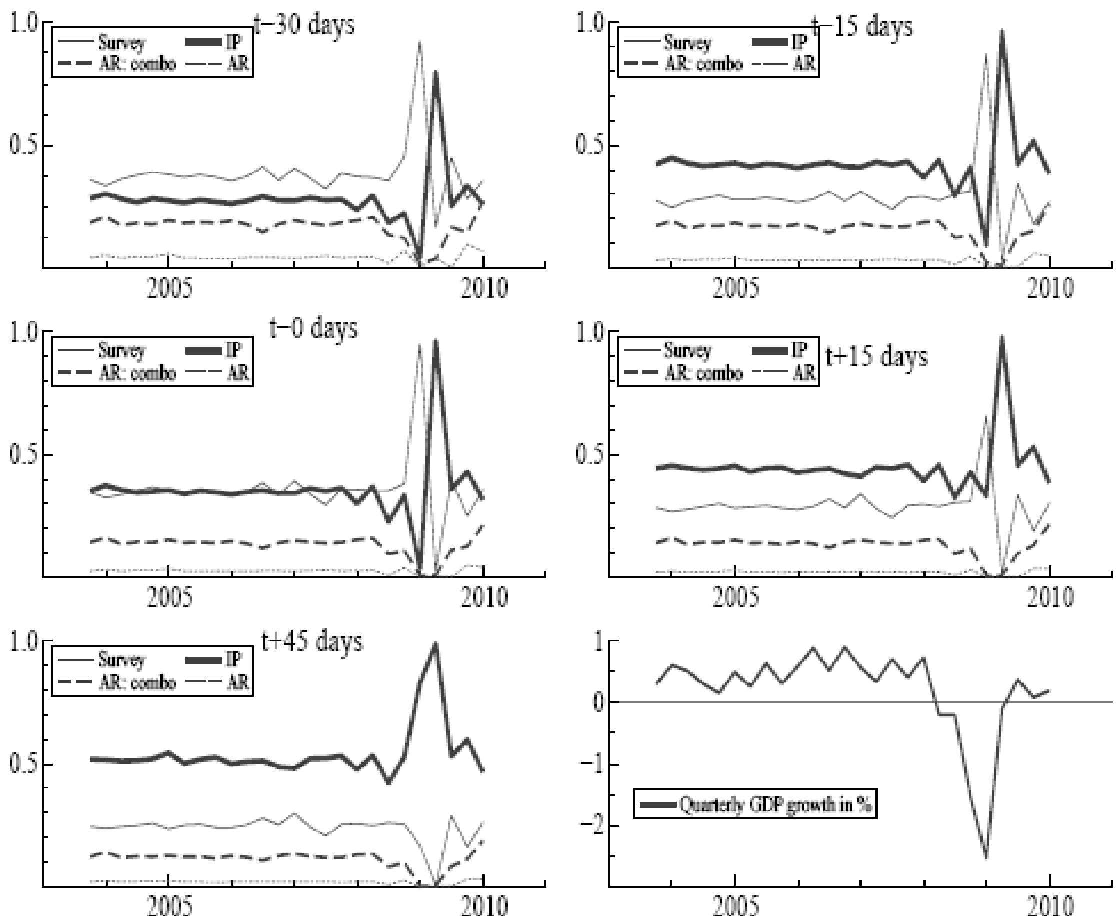
- the weight on IP increases as j increases: more hard data available, higher weight in the combined density (improvement out-of-sample density fit)

- At t+15 days IP weight increases dramatically relatively to survey data, approaching one at end of evaluation period
- But during the *recession*, weights of soft data increases at t-30, t-15 and t+0, close to unity during the depth of the recession. While weights on IP declined rapidly during the recession and rose as it ended. From t+15, weight remains high on IP data even over the recessionary period.
- AR hard to beat when point nowcasting. With density nowcasting, weights of AR components non negligible, although declining as within quarter information accumulates: at t+45 less than half the weight than t-30.

There is always an issue about how to choose the length of the training period to calibrate the weights. In fact, there is a trade-off involved. The shorter the length of the training period the more quickly the combined density can adjust to changes over time in the performance of the different models. But the longer the length of the training period the better the combination weights are estimated.

Figure 2 shows the recursively computed log score weights.

Figure 2: **Recursive log score weights**



Source: Authors' calculations

In fact, figure 2 shows more clearly than figure1 that:

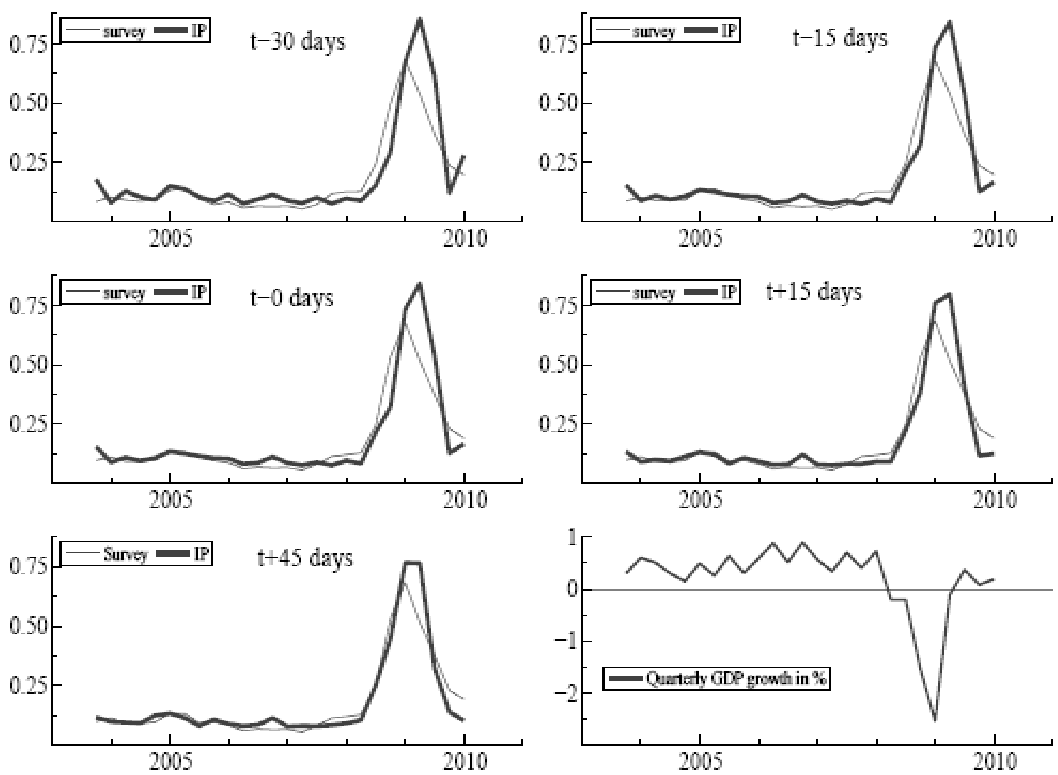
- informational content of survey data increased suddenly during 2008
- Soft data picked up the recession more quickly than hard IP data
- When IP data published, at t+45 days, survey data do not increase in importance during the recession
- how the weight on the IP data increases as j increases.

Finally interesting results are also shown by the figure 3 and 4: Probability of recession.

Figures 3 and 4 extract from density nowcasts the implied probability of a (one period) recession. It is evident that:

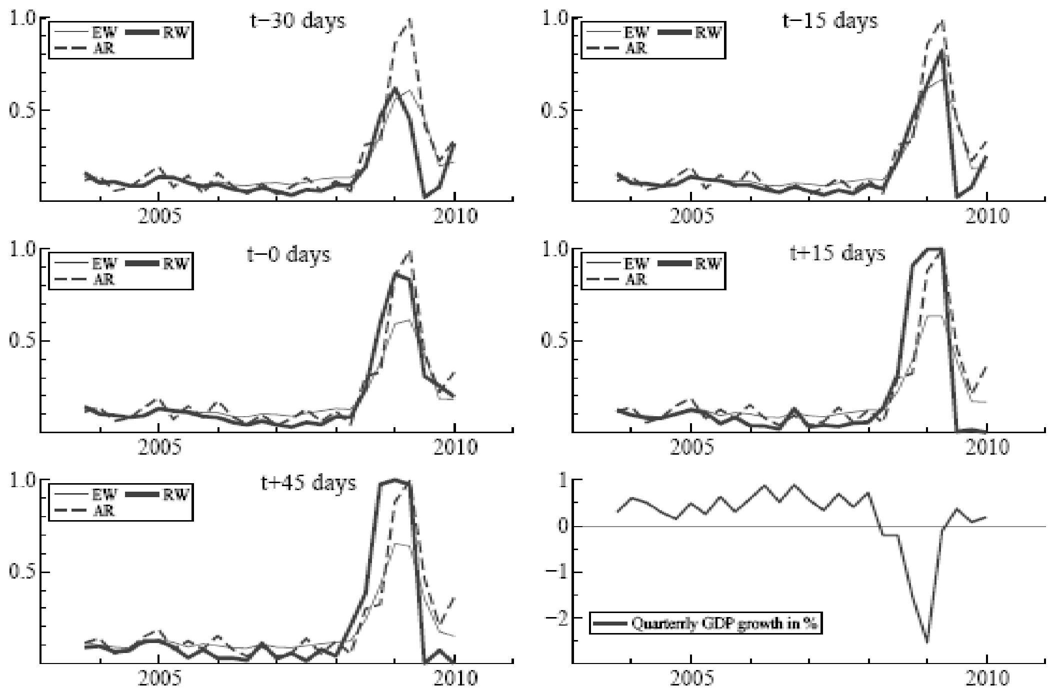
- RW combined densities pick up earlier the recession than hard IP data, as increasingly put higher weight on soft data during the recession
- Soft data also correctly picked up the end of recession in Euro Area in a way not predicted by the combined densities. Their dependence on history to tune the weights means that they cannot adjust as quickly as soft data
- *But* on average over the evaluation period, nowcast density produced by survey data alone is not well calibrated
- Waiting for second month's IP data, RW combined densities clearly anticipate both the beginning and the end of recession earlier than EW combined density.

Figure 3: **Implied probability of recession: survey and IP data**



Source: Authors' calculations

Figure 4: Implied probability of recession: EW, RW and AR combined densities



Source: Authors' calculations

All in all, what emerges from this application is that the relative importance of indicator variables switched suddenly in the recession. In fact, during recession, soft data were more informative than hard data on IP (when nowcasting with one month of within quarter information on IP available). It is also important the length of period used to tune the weights in combined densities: when abrupt switch in utility of different indicator variables, equal weighted combined densities deliver more accurate density nowcasts than recursive weighted ones. Equal weighted are more robust to uncertain instabilities, which are particularly acute nowcasting earlier within the quarter. At t+15 days, with second month of within quarter IP data published, recursive weighted combined densities become more competitive because it shifts more weight, during recession, from IP data to the forward-looking survey data.

2.3 Increasing data timeliness: Coincident indicators

Coincident indicators aim to forecast the evolution of economic variables during the reference period or just after it. For this purpose, they are based on same principles of leading indicators. The main advantage of coincident indicators is that they are subject to fewer constraints than flash estimates, even if, once again, the use of economic relationship is not recommended. In more recent years, we have investigated alternative model specifications for GDP, IPI and more recently Employment. The results for the IPI are not very satisfactory also because of the high degree of volatility of this indicator. In this paper we briefly present our approach to construct a coincident indicator of GDP.

We have used several models, belonging to the same category: regression models. They differ in the type of regressors they embed: individual series in bridge models against principal components in factor models. At the beginning bridge models were preferred to factor ones because they were based on as large data set as possible. Afterwards, our interest was focussed on the type of data to be included in the models: soft data only or a combination of soft and hard data (i.e. IPI growth rate, also one financial variable is included euro/dollar exchange rate (in growth rate)).months ahead.

Indeed, recent development in the area of factor models pointed out that factor extraction could be better based on small data set than large one. This led us to produce factor models, and we run on real time data.

The factor models are built in the spirit of Stock and Watson (2002). Namely a data set is reorganised into principal components. These factors are introduced in a regression to explain the target (for example, GDP growth) and the statistically significant factors are kept in the regression. The main difference between our factors models and the Stock and Watson ones is the size of data set, we use small dataset whereas principal components are usually extracted form a large data set. The principal components extraction is carried out on standardized data, firstly stationarized if necessary. We then regress the target (GDP growth) on these principal components and an intercept. We finally select the significant principal component and add financial data to these factors.

The very first factor models were constructed on small data set and being the data series chosen by subjective criterion based on past experience. Afterwards, we introduced a more objective data selection process, using the LARS algorithm recommended (presented) by Bai and Ng (2008), The LARS algorithm is selecting the targeted predictors (i.e. the most appropriate variables to estimate the quarterly GDP) not too aggressively as other stepwise algorithms do, in fact it allows keeping correlated series which is desiderable when the final objective is to extract principal components. No series of the data set are eliminated; they are all ranked by decreasing predictive power according to the selection criterion of the LARS algorithm.

However, we used the LARS algorithm with some differences from Bai and Ng one. Firstly, some series are introduced several times in the data set (with different lags) as we expect the LARS algorithm will show coincident or leading features of the series. Secondly, soft data series can be introduced both in levels and variation. That can help to forecast; the LARS algorithm is able to rank rapidly a large number of series starting form the most predictive one to the less. Final difference is that principal components are extracted from a dataset containing no financial series, which is introduced directly in the regression (we in fact observed frequently financial series generates on its own on principal component).

We have built and compared three different models: 1) a bridge model containing hard and soft data (named BHS), 2) a first factor model, with factors built with soft and hard data (named FHS), 3) a second factor model, with factor constructed exclusively with soft data (named FS). The latter is built in order to estimate coincident GDP growth when no hard data is available for the quarter.

The bridge model includes the Industrial Production Index, Construction Output Index, Consumer opinion over next 12 months, Employment expectations in construction, Construction confidence indicator and the euro/dollar real exchange rate.

The factor models include survey data (Industry, Consumers, Construction, Retail Trade) and hard data (Industrial Production excluding construction, Construction production, exports, retail sales and unemployment rate)

For each quarter we produce three estimates of GDP: the first at the end of the second month (t-30), the second at the end of the quarter (t+0) and the last one at the end of the first month of the next quarter (t+30).

The following table shows the real time results obtained by using the three models for data selection over the period Q4 2005 – Q3 2010, complemented by the LARS algorithm from 2009. We compare the three estimates of the coincident indicator to the Eurostat flash. The results appear very encouraging.

At t-30 days, estimates are carried out by the factor model with soft data (FS). We can observe that only three quarters are poorly estimated: Q1 2008 and, during the crisis, Q4 2008 and Q1 2009. In those two quarters, there is an over estimation: survey data cannot track the strong fall in GDP. At t+0 and t+30 days, we can see that the magnitude of the recession (2008Q4, 2009Q1) has not been correctly anticipated whatever the model. We note an unusual size of the error between the estimates of the coincident indicator and Eurostat flash one. However the two models including hard data predict better than the FS the 2009 Q1 fall. Globally, the factor model (*FHS*) gives better results than the bridge model (*BHS*). In general, the coincident indicators anticipate correctly the GDP growth in most cases. Further simulations are required, but the coincident indicator presented appears to be robust and reliable enough.

Table 3: Coincident Indicator of GDP growth

End of Quarter *T*	Models	Estimates *T*–30	Estimates *T*+0	Estimates *T*+30	Eurostat Flash *T*+45
2005Q4	FS BHS FHS	0.65	0.72 0.50 0.41	0.72 0.58 0.47	0.31
2006Q1	FS BHS FHS	0 .77	0.82 0.83 0.81	0.82 0.80 0.78	0.59
2006Q2	FS BHS FHS	0.93	0.97 0.81 0.89	0.97 0.90 0.87	0.88
2006Q3	FS BHS FHS	0.65	0.69 0.73 0.74	0.72 0.82 0.89	0.52
2006Q4	FS BHS FHS	0.68	0.67 0.49 0.69	0.66 0.41 0.69	0.90
2007Q1	FS BHS FHS	0.52	0.55 0.50 0.59	0.55 0.49 0.53	0.57
2007Q2	FS BHS FHS	0.56	0.57 0.32 0.53	0.57 0.28 0.47	0.34
2007Q3	FS BHS FHS	0.75	0.66 0.76 0.72	0.65 0.96 0.93	0.71
2007Q4	FS BHS FHS	0.35	0.34 0.32 0.38	0.34 0.33 0.43	0.41
2008Q1	FS BHS FHS	0.12	0.13 0.28 0.43	0.13 0.41 0.55	0.79
2008Q2	FS BHS FHS	0.09	0.03 0.13 0.06	0.02 0.02 –0.03	–0.20
2008Q3	FS BHS FHS	–0.25	–0.35 –0.33 –0.25	–0.35 –0.09 –0.09	–0.19

Source: Authors' calculations

Table 3: Coincident Indicator of GDP growth (cont.)

End of Quarter T	Models	Estimates T–30	Estimates T+0	Estimates T+30	Eurostat Flash T+45
2008Q4	FS BHS FHS	–0.72	–0.99 –0.91 –0.89	–0.99 –1.06 –1.10	–1.46
2009Q1	FS BHS FHS	–0.95	–1.00 –1.40 –1.56	–1.06 –1.48 –1.63	–2.55
2009Q2	FS BHS FHS	–0.61	–0.45 –0.76 –0.56	–0.45 –0.59 –0.51	–0.10
2009Q3	FS BHS FHS	0.32	0.23 0.36 0.19	0.40 0.74 0.35	0.40
2009Q4	FS BHS FHS	0.52	0.57 0.20 0.25	0.57 0.35 0.33	0.10
2010Q1	FS BHS FHS	0.41	0.46 0.75 0.38	0.46 0.90 0.46	0.19
2010Q2	FS BHS FHS	0.40	0.68 0.65 0.48	0.68 0.87 0.77	0.97
2010Q3	FS BHS FHS	0.58	0.69 0.79 0.70	0.68 0.70 0.60	0.34
2010Q4	FS BHS FHS	0.38	0.48 0.58 0.60	0.48 0.60 0.62	0.29
2011Q1	FS BHS FHS	0.61	0.65 0.63 0.54	0.65 0.64 0.58	0.83
2011Q2	FS BHS FHS	0.24	0.24 0.44 0.46	0.24 0.44 0.46	0.17
2011Q3	FS BHS FHS	0.06	-0.06 -0.02 0.01	-0.05 0.41 0.34	-

Source: Authors' calculations

3. A system of euro area monthly indicators of economic activity

The GDP is obviously the ideal candidate as reference variable for short-term and business cycle analysis but, unfortunately, it is only available at quarterly basis and the production of a monthly GDP, completely based on National Accounts standards, appears still not feasible. For this reason, several studies have been recently conducted to investigate alternative ways to construct monthly proxies of GDP. Examples of such indicators are available in Sweden, Finland, Estonia, U.K. as well as Canada. From 2006 onwards, we have investigated the possibility of constructing a euro area monthly indicator of economic activity as much as possible consistent with the GDP, called EuroMIND. The availability of a monthly indicator disaggregated into branches of activity such as EuroMIND is particularly relevant to monitor the business cycle in real time. EuroMIND allows following in real time the evolution of the different elements of the euro area economy: sectors and demand components.

The EuroMIND methodology is presented in detailed way in Frale et al. (2011) and can be synthetically described as follows:

1. We base the construction of the monthly indicator of economic activity on a disaggregate approach represented by the output and expenditure breakdowns of the GDP at quarterly base;
2. For each disaggregate GDP component, a set of monthly indicators are carefully selected, including both macroeconomic variables and survey answers;
3. The indicator is based on information at both monthly and quarterly level, rather than monthly only, modelled with a dynamic factor specification cast in state-space form. In this step for each component of GDP a composite coincident indicator based on dynamic factor analysis is estimated ;
4. The state space methodology has the flexibility of handling data with different frequency of observations. This is achieved by suitably defining the states of the system so as to convert temporal aggregation into a systematic sampling problem;
5. Since estimation of the multivariate dynamic factor model can be numerically complex, computational efficiency is achieved by implementing univariate filtering and smoothing procedures;
6. Special attention is paid to chain-linking and its implications for the construction of a monthly indicator of economic activity, via a multistep procedure that exploits the additivity of the volume measures expressed at the previous year prices;
7. The estimate of the euro area monthly indicator of economic activity is obtained by combining the estimates from the output and expenditure sides, with optimal weights reflecting their relative precision;
8. The resulting pooled estimator is more precise than each of its two components, paralleling the results on the usefulness of pooling in the forecasting literature. The resulting estimates are benchmarked to quarterly national accounts produced by Eurostat so that the full consistency between monthly and quarterly estimates is achieved;
9. We provide an explicit measure of uncertainty around the indicator, which is particularly relevant in a decision making context and for evaluation purposes.

3.1 The dynamic factor model, its statistical treatment and temporal disaggregation

The modelling strategy mentioned at point 3) refers to the Stock and Watson (1991) SW *single index model*. The fundamental idea behind this specification is to separate the dynamics which are common to a set of N coincident series, y_t, that are $I(1)$ but not cointegrated, from the idiosyncratic component, which is specific to each series. The level specification of the SW *single index* model here considered expresses y_t as the linear combination of a common cyclical trend, that will be denoted by μ_t, and an idiosyncratic component, $\boldsymbol{\mu}^*_t$. Letting ϑ_0 and ϑ_1 denote $N\times 1$ vectors of loadings, and assuming that both components are stationary in first difference and subject to autoregressive dynamics, we can write:

$$y_t = \vartheta_0 \mu_t + \vartheta_1 \mu_{t-1} + \boldsymbol{\mu}^*_t + \boldsymbol{B}\boldsymbol{x}_t, \qquad t = 1, \ldots, n,$$
$$\varphi(L)\Delta\mu_t = \eta_t, \quad \eta_t \sim NID(0, \sigma_\eta^2), \qquad (10)$$
$$\boldsymbol{D}(L)\Delta\boldsymbol{\mu}^*_t = \boldsymbol{\delta} + \boldsymbol{\eta}^*_t, \quad \boldsymbol{\eta}^*_t \sim NID(\boldsymbol{0}, \boldsymbol{\Sigma}_{\eta^*}),$$

where $\varphi(L)$ is an autoregressive polynomial of order p with stationary roots

$$\varphi(L) = 1 - \varphi_1 L - \ldots - \varphi_p L^p \ldots \qquad (11)$$

and the matrix polynomial $\boldsymbol{D}(L)$ is diagonal:

$$\boldsymbol{D}(L) = diag[d_1(L), d_2(L), \ldots, d_N(L)] \qquad (12)$$

with $d_i(L) = 1 - d_{i1}L - \ldots, d_{ip}L^p$ and $\boldsymbol{\Sigma}_{\eta^*} = diag(\sigma_1^2, \ldots, \sigma_N^2)$. The vector $\boldsymbol{x}_t$ contains the value at time t of k deterministic regressors common to all the series, e.g. trading days and moving festivals regressors, and $\boldsymbol{B}$ is an $N \times k$ matrix of regression coefficients. The disturbances η_t and $\boldsymbol{\eta}^*_t$ are mutually uncorrelated at all leads and lags.

The lag polynomial $\vartheta_0 + \vartheta_1 L$ can also be rewritten as $\boldsymbol{\theta}_0 + \boldsymbol{\theta}_1\Delta$, where $\boldsymbol{\theta}_0 = \vartheta_0 + \vartheta_1$ and $\boldsymbol{\theta}_1 = -\vartheta_1$. The measurement equation can thus be reparameterised as

$$y_t = \boldsymbol{\theta}_0 \mu_t + \boldsymbol{\theta}_1 \Delta\mu_t + \boldsymbol{\mu}^*_t + \boldsymbol{B}\boldsymbol{x}_t \qquad (13)$$

The model postulates that each series, in differences, Δy_{it}, is composed of a mean term δ_t, an individual AR(p^*) process, $d_i(L)^{-1}\eta^*_{it}$, and a common AR(p) process, $\varphi(L)^{-1}\eta_t$. Both μ_t and $\boldsymbol{\mu}^*_t$ are difference stationary processes and the common dynamics are the results of the accumulation of the same underlying shocks η_t; moreover, the process generating the index of coincident indicators is usually more persistent than a random walk and in the accumulation of the shocks produces cyclical swings.

Notice that (1) assumes a zero drift for the single index and a unit variance for its disturbances is also assumed. These identification restrictions can be removed at a later stage to enhance the interpretability of the estimated common index (we may alternatively restrict to unity one of the loadings in $\boldsymbol{\theta}_0$ and include a nonzero drift in the common index equation, provided we impose one linear constraint on β).

The estimation of the model parameters, the factors and the disaggregate GDP monthly component series is carried out by using the state space methodology (see Harvey, 1989).

The dynamic factor model (1) can be cast in state space form, consisting of a measurement equation, relating the monthly series to a set of latent states (representing the latent factors and their lags), and a transition equation, describing the dynamic evolution of the states. The basic state space representation has to be modified so as to take into consideration the observational constraints imposed by temporal aggregation. The latter is such that we do not observe the monthly values of the GDP components, but only their sum across a quarter. Suppose that the set of coincident indicators, y_t, can be partitioned into two groups, yt = [$y_{1,t}^{'}$, $y_{2,t}^{'}$]′, where the second block gathers the flows that are subject to temporal aggregation, so that

$$y_{2\tau}^{*} = \sum_{i=0}^{\delta-1} y_{2,\tau\delta-i}, \ \tau = 1, 2, [T/\delta] \qquad (14)$$

where δ denote the aggregation interval: for instance, if the model is specified at the monthly frequency and $y_{2,t}^{*}$ is quarterly, then δ = 3.

The modified state space form is defined in terms of a partially cumulated monthly series, subject to missing values, that converts temporal aggregation into a systematic sampling problem. The cumulator variable, $y_{2,t}^{c}$, is defined as follows

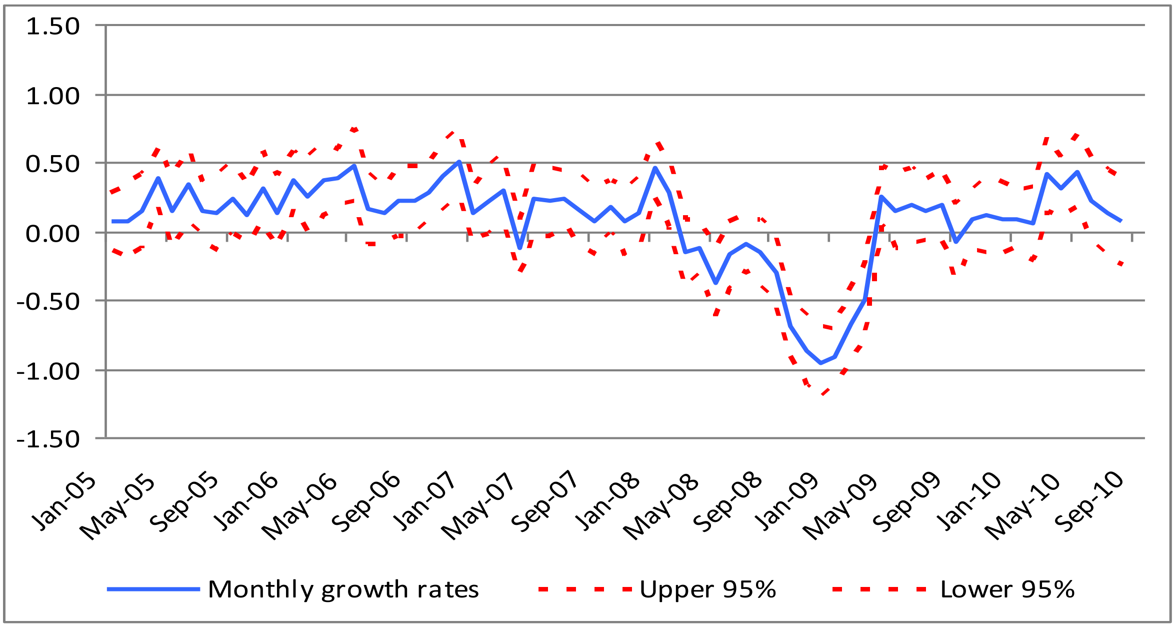
$$\begin{aligned} y_{2,t}^{c} &= \psi_t y_{2,t-1}^{c} + y_{2,t} \\ \psi_t &= \begin{cases} 0 & t = \delta(\tau-1)+1, \tau = 1,\ldots,[n/t] \\ 1 & \text{otherwise} \end{cases} \end{aligned} \qquad (15)$$

Notice that at times t = δτ the cumulator coincides with the (observed) aggregated series, otherwise it contains the partial cumulative value of the aggregate in the seasons (e.g. months) making up the larger interval (e.g. quarter) up to and including the current one.

The Kalman filter for this state space representation enables the evaluation of the likelihood via the prediction error decomposition. This opens the way to maximum likelihood estimation of the unknown parameters by a quasi-Newton optimisation algorithm. Conditional on the maximum likelihood estimates and the available observations, the estimation of the unobserved components and the missing values (and thus the disaggregated series) is carried out by a suitable smoothing algorithm. For computational efficiency, the Kalman filtering and smoothing equations are implemented using sequential processing (see Anderson and Moore, 1979, and Koopman and Durbin, 2000).

Figure 1 presents the growth rate of Euro-MIND from January 2005 to September 2010 as estimated in November 2010, together with their confidence interval at 95%. Looking at the graph, it is important to note that the evolution of the indicator is quite regular and it follows very well the cyclical movements. The estimates appear very stable and not volatile, that is also confirmed by analysing subsequent vintages for the same period. The main point on which the indicator still needs some improvements is represented by its behaviour in estimating the month of the current quarter especially in the recession phase. Our indicator delivers negative growth rates (e.g. January and February 2009), which appear too optimistic in comparison with the expected results. A most accurate specification of the model for the financial services sector and for the demand side component will probably improve the ability of the model to estimate the most recent months.

Figure 5: EuroMIND Growth rate on previous month



Source: Authors' calculations

3.2 Extensions of EuroMIND and ongoing activities

In order to better exploit the characteristics of EuroMIND taking into account particular events as powerful tool for the assessment of the economic situation, several extensions have been developed or are currently under development. The first one is the generalization of this model with better forward looking properties and brings to the production of the EuroMIND-S indicator, based on the incorporation of surveys data. Survey data represent a very timely piece of economic information which originates from the quantification of qualitative survey questions, asking firms and consumers opinions on the state of the economy EuroMIND-S is obtained using two factors in the construction of the composite indicators described in step three, where the second one contains business and consumer surveys data. EuroMIND-S is presented in Frale at al. (2010); this version of EuroMIND increases its nowcasting and forecasting abilities at one-two-three steps ahead thanks to the fact that business and consumer surveys data are modelled as a separate factor from hard data. In fact, if both hard and soft data are modelled in a single factor, soft data are dominated by hard ones so that their contribution to the model results to be almost zero.

A real-time simulation of the one factor based model has been carried out since 2006 with very encouraging results. In this simulation we are producing estimates at t+45 each month, so that at month t we produce the estimate for month t-2. At the same point in time, estimates for the month t-1, t, t+1 can be obtained by using the two factors version of the model.

A second extension of EuroMIND, called EuroMIND-C, is constructed by jointly estimating a monthly indicator of economic activity at euro area and member state level, in order to asses the relevance of national information to increase the reliability of euro area estimates. EuroMIND-C is based on a parametric large scale factor model handling a very large set of time series with mixed frequency and subject to missing values, featuring more than 150 monthly time series and 55 quarterly national accounts series concerning the decomposition of gross domestic product according to the output and expenditure approaches. The time series refer to the Euro area as a whole and to the four largest countries (Germany, France, Italy and Spain). From the methodological point of view, a novel state space representation is adopted for a dynamic factor model which models jointly the series for the countries and the sectors of the economy, and a new treatment of missing values and temporal aggregation is introduced. One of the most important results is the availability of the monthly indicator of GDP, disaggregated by sector and country, which provides a timely and accurate assessment of the state of the Euro area economy for the period January 1995-October 2010. Thanks to this indicator an analysis of co-movements between different countries cycles is possible also at sectoral level, showing for example as the last recession started earlier in the industry and trade sectors, although there is no common pattern in the construction sector across the mentioned countries.

Furthermore, the availability of a long time series for an indicator of euro area economic activity would be of great relevance in the elaboration of models for dating and detecting turning points. In particular, when checking the fitness of the model it is necessary to have data whose length spans over more than one economic cycle. Unfortunately, official statistics are naturally subject to major revisions, such as changes in definitions or classifications, which often cause disruptions and a reduction in the time series length. In order to overcome such drawback, techniques for the reconstruction of long time series for key economic indicators, based on the largest possible information set and on simple and robust methodology and their application to EuroMIND have been investigated too. Nevertheless the exercise is still quite challenging because before the eighties many source of information used in the EuroMIND model were not available,even when restricting the exercise to the aggregated EuroMIND excluding its components.

4. Euro area turning point detection

The set of macroeconomic statistics regularly compiled by a statistical office represents a very useful instrument available to all users and analysts. Nevertheless, we have to recognise that not all the information needed by analysts is explicitly available from an investigation of statistics. Some signals need to be extracted in order to have a clearer picture of the cyclical evolution of the economy, complementing the information supplied by statistics. In this context, we have decided to launch several activities aiming to the definition of a coherent statistical framework for business cycle analysis. They include the construction of statistical turning point chronologies, the development of turning point coincident indicators and of growth cycle estimates (i.e. output gap in the case of GDP), which can support economic monitoring and decision making processes.

The methodology for the construction of a euro area turning point chronology and a system of coincident turning point indicators is presented in Anas at al. (2008). The methodology can be synthetically expressed by the following points:

1) simultaneous analysis of classical business cycle and growth cycle in the so called ABCD framework;

2) statistical dating of euro area turning points by means of a simple non parametric dating rule;

3) comparison of euro area and Member States dating to achieve a final statistical chronology ensuring the maximum degree of consistency between the two approaches. In this context we also investigate the synchronisation of turning points between euro area and member states and their diffusion. Some descriptive measures of cyclical movements such as length of cycle, deepness etc are also produced. The chronology is updated on quarterly basis;

4) preliminary investigation of alternative models for the construction of turning point composite coincident indicators for classical business cycle and growth cycle, including the identification of appropriate number of regimes and thresholds;

5) variable selection performed on the basis of the ability of a set of potential candidates series to correctly detect growth cycle turning points. For each series a set of transformations has been applied in order to choose the most appropriate one. After this exploratory investigation five variables have been identified of the component of the gross cycle Turning point composite coincident indicators: Employment expectation, Construction confidence indicator, Financial situation of the last 12 months, IPI, Imports of intermediate goods;

6) construction of the growth cycle coincident indicators (GCCI) as a weighted mean of the transition probability returned by the five univariate two regimes Markov Switching models fitted on each variable as it is shown in formula ( ) below:

$$GCCI_t = \frac{1}{5}\sum_{k=1}^{5} \Pr(\text{Recession})_t^k , \qquad (16)$$

where $\Pr(\text{Recession})_t^k$ is the probability that the *k – th* component of the GCCI is in a recession of the growth cycle at time *t*, with $k \in \{1,2,3,4,5\}$.

An equal averaging weighting scheme is used.

A K-regime Markov-Switching process, denoted by MS(K) – AR(p), can be defined by the following equation:

$$Y_t - \mu(S_t) = \sum_{i=1}^{p} \phi_i(S_t)(Y_{t-i} - \mu(S_{t-i})) + \sigma(S_t)\varepsilon_t, \qquad (17)$$

where the non-observed process (St)t is an ergodic Markov chain of the first order and where (εt)t is a standardized white noise process; the parameters describe the dependence of the process (Yt)t to the current regime St.

The associated transition probability of the process (St)t is defined by:

$$\Pr[S_t = j | S_{t-1} = i] = p_{ij} \qquad (18)$$

For each release and each model the QPS and Concordance Index are computed as follows.

$$QPS = \frac{1}{T}\sum_{t=1}^{T}(P_t - RC_t)^2, \qquad (19)$$

where, for $t \in \{1,\ldots,T\}$, P_t is the filtered probability of being in recession in month t and

$$CI = \frac{1}{T}\left[\sum_{t=1}^{T} I_t \times RC_t + \sum_{t=1}^{T}(1-I_t)\times(1-RC_t)\right], \qquad (20)$$

where is the same variable already employed in the QPS, which represents the turning points of the reference chronology, while is a binary random variable that assumes value 1 if the coincident indicator is in the recessionary phase of the business cycle and 0 otherwise.

7) the variable selection has been performed on the basis of the ability of a set of potential candidates series to correctly detect gross cycle turning points. For each series a set of transformations has been applied in order to choose the most appropriate one. After this exploratory investigation five variables have been identified of the component of the gross cycle Turning point composite coincident indicators: IPI, New cars registration and Unemployment rate;

8) construction of the business cycle coincident indicators (BCCI) as a weighted mean of the transition probability returned by the three univariate three regimes Markov Switching models fitted on each variable as it is shown in formula ( ) below:

$$BCCI_t = \sum_{k=1}^{3} \omega^k \Pr(\text{Recession})_t^k, \qquad (21)$$

where is the probability that the k – th component of the BCCI is in a recession of the business cycle at time t and is the weight given to it, with .

The following weighting scheme is used IPI=0.34, Unemployment rate=0.46, New cars registration=0.20.

Filtered probabilities can be viewed as the probabilities of being in a recession phase delivered by each component of the indicators. Indicators deliver the joint recession probabilities. Higher value of the indicator corresponds to high probability of being in a recession. The threshold (set at 0.5) corresponds to a decision rule: values exceeding the threshold indicate recession phase, values below the threshold correspond to an expansionary phase.

A real time simulation of the two indicators against respectively the business cycle and growth cycle chronology has been carried out to check the reliability of the models as well as to discover possible false signals. The main results are that the two indicators do not show any significant evidence of false signals and that they are slightly lagging with respect to the corresponding chronologies. Each month we produce estimates of business cycle coincident indicators and growth cycle coincident indicators for the month t-2, based on filtered probabilities. Estimates for the month t-1 and t are based on forecasted probabilities. Figures 2 and 3 show the behaviour of the two indicators GCCI and BCCI as estimated in November 2010. In both graphs the black bold line is the constant threshold equal to 0.5. When the indicators deliver values higher than 0.5 we are respectively in a growth cycle or business cycle recession phase. On the contrary when the indicators deliver values below 0.5, we are in an expansion phase for both cycles. The blue lines show the values of the two indicators obtained by averaging the filtered probabilities of the components. The red part at the end of the line corresponds to the value obtained by averaging forecasting probabilities instead of filtered ones. Looking at the indicators, the negative phase for the growth cycle started in April 2007 and ended in September 2009 (see Fig. 1). Concerning the business cycle, the recession started in October 2008 and ended in September 2009 (see Fig. 3). As already mentioned both indicators appear to be slightly lagging and this is particularly true for the BCCI. In fact, nowadays we are thinking that the business cycle recession has started in the first half of 2008. From this point of view is obvious that BCCI still needs some improvements. Nevertheless, it has to be noted that it is preferable to have indicators detecting later turning points than ones delivering false signals or anticipating too much turning points.

In order to announce the cyclical monitoring of the euro area, several initiatives have been recently undertaken and some of them are still ongoing. The first one concerns the extension the cyclical monitoring also to the acceleration cycle (also referred as gross rate cycle) following the approach α AB ß CD. The chronology of these three cycles has already been assessed and a first attend to construct turning point composite coincident indicator for the acceleration cycle is still ongoing. In order to improve the timeliness of BCCI and GCCI we have investigated also other non-linear specifications based on SETAR models. An extensive real time comparison of indicators based on Markov Switching models and SETAR models has been carried out. The main outcome of this simulation can be synthesised as follow:

1. SETAR models are slightly more timely than MS one.

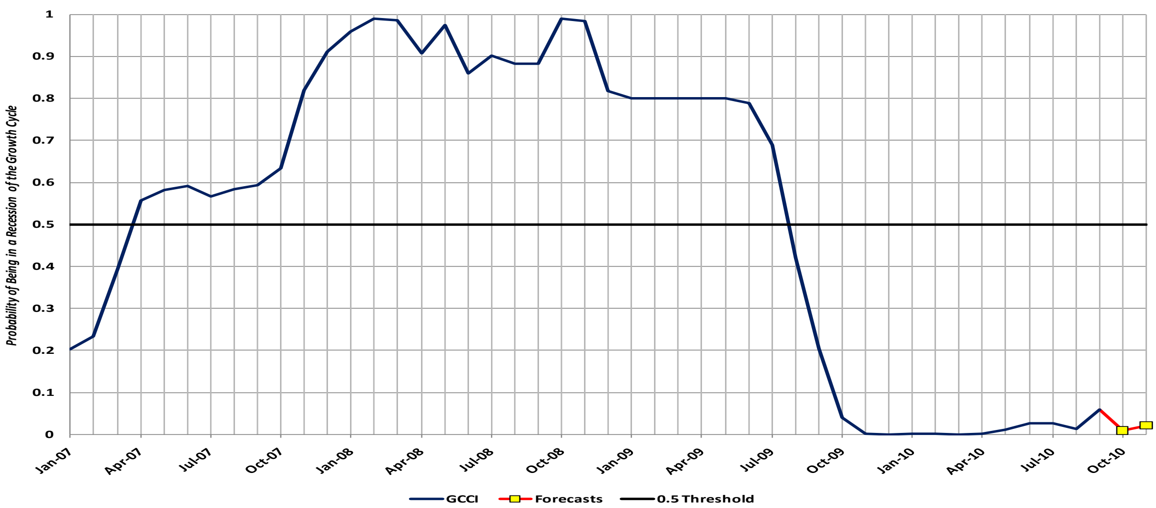
2. the number of false signals returned by SETAR models is higher than in the case o Markov Switching ones even when a censoring rule is applied.

3. composite indicators based on SETAR models are less stable over the time than those based on Markov Switching ones. For this reason it has been decided that SETAR model could only be used as to complement the information supplied by Markov Switching ones but that they couldn't replace them. The main results of this study are presented in Anas, Billio, Ferrara, Mazzi (paper presented at the 6th Colloquium on modern tools for business cycle analysis). The effect of alternative seasonal adjustments methods on detecting turning points as well as the behaviour of a composite coincident indicator for Turning point based on non-seasonally adjusted data have also been analysed in real time in a paper by Billio, Ladiray, Mazzi, Montana (paper presented at the 6th Colloquium on modern tools for business cycle analysis). The main outcome of this study is that the use of a common seasonal adjustment method for all component of the composite indicator is preferable with respect to the use of various seasonal adjustment methods.

Furthermore the composite indicator based on non-seasonally adjusted data has given in the case of gross cycle, interesting results which open a new interesting field of investigation. Finally since some months, we are investigating the possibility of using a multivariate Markov Switching model to construct simultaneously composite coincident indicator for the growth cycle and the business cycle. This approach, among others, has the advantage of explicitly imposing the constraints derived by the ABCD approach. Preliminary results of this work appear very encouraging and we are planning to finalise this experimental phase beginning of the 2011.

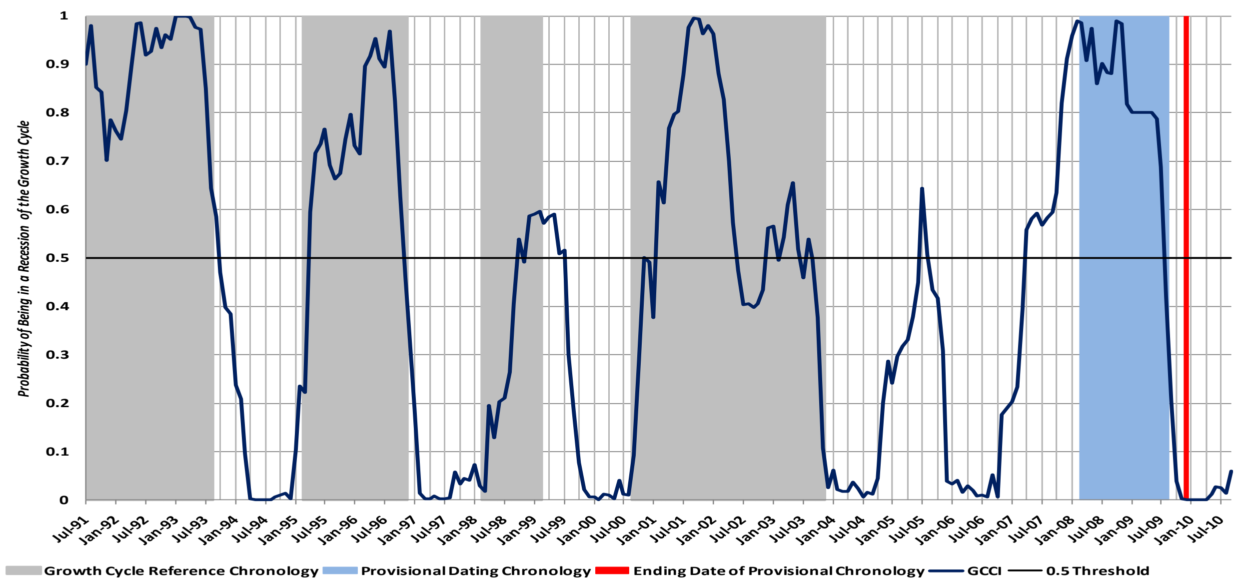
In case where the results will appear very positive the new multivariate approach will be used in the regular production and it will replaced the two univariate composite indicators presented above.

Figure 6: Growth Cycle Coincident Indicators



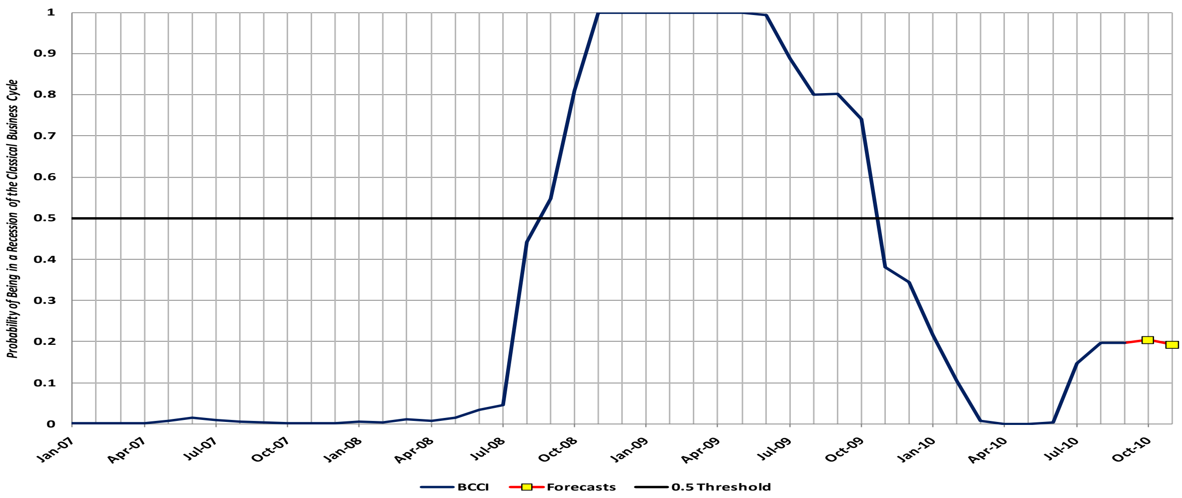
Source: Authors' calculations

Figure 7: Growth Cycle Coincident Indicators



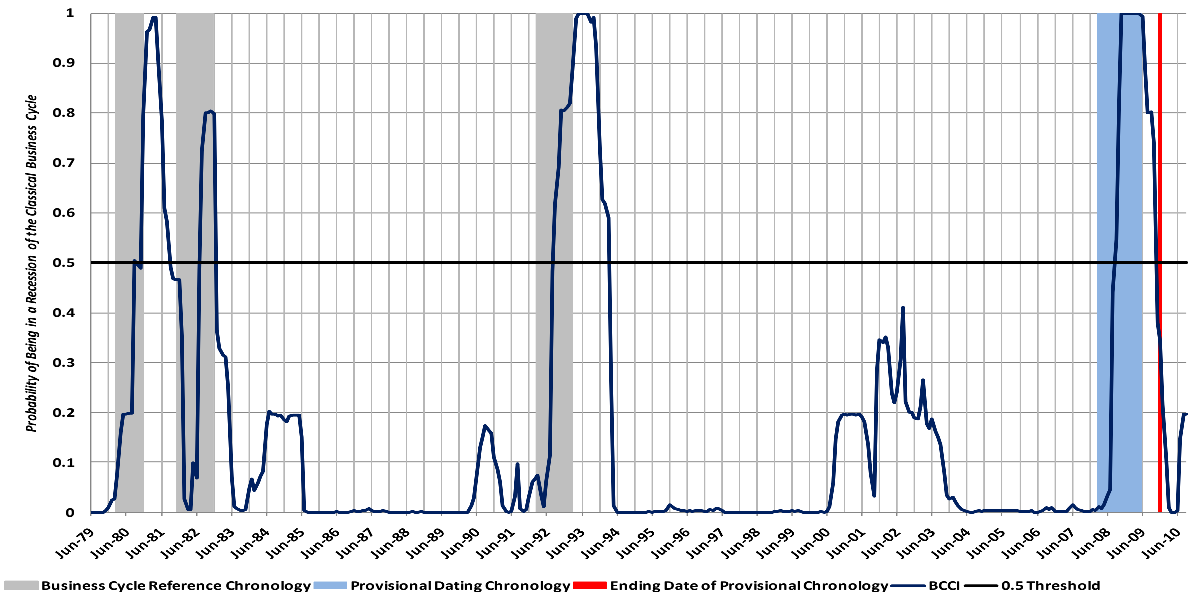
Source: Authors' calculations

Figure 8: Business Cycle Coincident Indicators



Source: Authors' calculations

Figure 9: Business Cycle Coincident Indicators



Source: Authors' calculations

5. Conclusions

In this paper we have presented, both from a theoretical and an empirical point of view, a number of econometric tools which can complement official infra-annual statistics and PEEIs in particular, in order to fill at least partially some of their gaps and consequently increase their relevance for policy and decision makers, as well as analysts an researchers. Based on the results shown in the paper, we can conclude that all these tools efficiently complement traditional official statistics in the desired direction, providing a powerful framework for data analysis and diagnosis.

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Advances in econometric tools to complement official statistics in the field of Principal European Economic Indicators

GIAN LUIGI MAZZI, FILIPPO MOAURO
AND ROSA RUGGERI CANNATA

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