Construction of coincident indicators for the euro area

Françoise Charpin (*), *Catherine Mathieu* (**), *Gianluigi Mazzi* (***)

June 2008

Abstract

The availability of timely and reliable information on main macroeconomic variables is considered both by policy makers and analysts as crucial for an effective process of decision making. Unfortunately official statistics cannot always meet adequately user needs. This is the reason why, using econometric techniques analysts try to anticipate or estimate in real time main macroeconomic movements. In this paper we compare several econometric models for the estimation of the period on period growth rate for the euro area Gross Domestic Product (GDP) and Industrial Production Index (IPI). This comparison is made on the basis of real time results provided by these models over six years (2002-2007). Tests of absence of bias are performed and Diebold-Mariano tests help us to select among the models.

JEL classification code: E37

Keywords: coincident indicators, GDP, industrial production, euro area

(*) OFCE Analysis and Forecasting Department, and University of Paris II

Email: francoise.charpin@ofce.sciences-po.fr

(**) OFCE Analysis and Forecasting Department

Email: catherine.mathieu@ofce.sciences-po.fr

(***) EUROSTAT, Responsible for Euro-indicators and statistical methodology

Email:Gianluigi.Mazzi@ec.europa.eu

1. Introduction

The availability of timely and reliable information on main macroeconomic variables is considered both by policy makers and analysts as crucial for an effective process of decision making. Unfortunately official statistics cannot always meet adequately user needs. This is the reason why, using econometric techniques analysts and statisticians try to anticipate or estimate in real time main macroeconomic movements. In this paper we compare several econometric models for the estimation of the period on period growth rate for the euro area Gross Domestic Product (GDP) and Industrial Production Index (IPI). This comparison is made on the basis of real time results provided by these models over six years (2002-2007).

The paper is organised as follows. Section 2 provides a description of the methodologies. Section 3 deals with data problems encountered. In Sections 4 and 5 real time analyses carried out with our approaches for euro area GDP are presented. Section 6 is devoted to IPI. Section 7 concludes.

2. A regression-based methodology

Actually, EUROSTAT releases a flash estimate of GDP for quarter T around the middle of the second month of quarter ($T+1$). We propose to produce a first estimate for quarter T at the end of the second month of quarter T, a second more reliable estimate at the end of the third month of quarter T and a third estimate, at the end of the first month of quarter ($T+1$). Several approaches are compared, all based on regressions using either individual series or principal components as regressors. Principal component regressions have become very popular since the article [4].

The selected regressors (individual series or principal components) can be classified into two groups, i.e. coincident or leading indicators. Leading indicators enter the regression with at least one lag and are thus entirely available at the date of the estimation. The inclusion of coincident regressors generates a difficulty because they are not entirely available at the time of producing the estimate. Hence they will have to be forecast. Thus coincident regressors will be chosen among survey data because they are rapidly available, with the exception of industrial production. Industrial production is a good candidate among explanatory variables because it is a good proxy of gross value added in the industry, which is still a relevant component of GDP and is used by many euro area countries to produce their flash estimates. When producing a coincident GDP indicator for quarter T, the missing months of industrial production of this quarter (3, 2 or 1) are forecast with a regression model described below. Concerning survey data, at most one month is missing for the first GDP estimate. We then use the average of the two available months as an estimate of the average of the three.

In previous work (see [2] and [3]) we ran three regression models with individual regressors in order to produce each month three GDP estimates, then averaged to provide a final GDP estimate. From this past experience, we select two regression models analysed in Section 4. Principal component regressions have also been investigated (see [2]) and given up because we found that they did not perform better than traditional regression models with individual series. We had then carried out the usual method of Stock and Watson (2002). In this paper (see annex 1), using real time data, we confirm again that this method can be discarded. Principal component regressions presented in Section 5 are carried out using a different method. Usually principal components (PC) are extracted from a large data set of coincident and leading series, all entering the data set without any lag. Then the most important PC are introduced in a regression model possibly with lags. It seems that the introduction of many series, more or less related to GDP, can produce a noise that deteriorates the estimate (see

[1]). Hence our suggestion is to consider only the series directly related to GDP growth[1], in principle those which can help to predict GDP growth but which cannot be introduced simultaneously in a regression because of multicollinearity. Moreover these series are lagged if they display leading properties in regression models. Thus, principal component regressions can be viewed here as a way to solve the multicollinearity problem. The information set is re-organized into principal components and only the significant ones will be kept in the GDP regression model. But, finally, this allows us to introduce all individual series from our data set[2], with their own either coincident or leading characteristics.

All results shown below are from a real time analysis run over the last six years (2002-2007). This means that all models used to estimate, for example, GDP growth of quarter *T* are run with data available during that quarter. We have been able to carry out such a real time analysis thanks to the EUROSTAT EuroInd database backup. Thus, even if these models did not exist in the past, it is possible to test their behaviour within a real time simulation exercise.

3. Data problems and their consequences

In the process of estimating different models, several data problems were encountered. First, the EUROSTAT euro area real GDP series currently starts from the first quarter of 1995 only. The shortness of the sample is a difficulty insofar as our first regressions used to estimate the first quarter of 2002, is based on a data span from the first quarter of 1995 to end at the fourth quarter of 2001. It has thus been necessary to back-recalculate real GDP series, which we have done up to the first quarter of 1992, using old GDP series in 1995 prices. We have then checked that our selected regressors remain significant if we start the estimation in 1995Q2, so as to make sure that our back-recalculation did not introduce false signals. While checking this, we have been led to give up interest rate variables in our models. These variables were the variation of the short interest rate with two quarter lags or the spread of interest rates (10 years minus 3 months) with two or three quarter lags, depending on the model. We observed that if our models were run over a period starting from 1993Q1 and later, all interest rate variables were not significant, while the opposite occurs over the period beginning in 1992Q2.

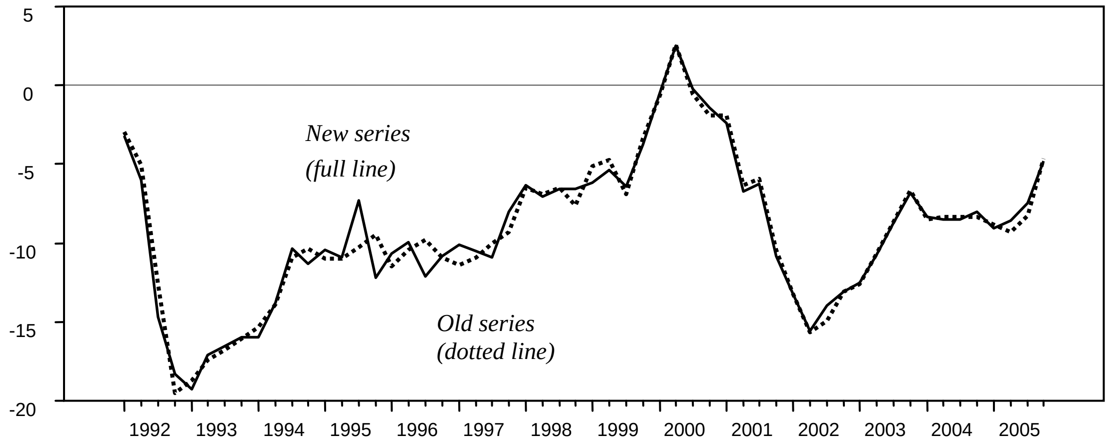
The second data problem comes from the retail survey. In principle survey data are not revised except for the most recent observations. In reality, survey series have known several changes, but the most important concerns the retail survey and occurred between the releases of October 2006 and November 2006 (see figure 1). We observed in our models that the degree of significance of the retail confidence indicator series was variable according to the estimation period, which is not surprising given the revisions. We decided to leave this survey out of our estimates because it did not seem fully reliable.

The third data problem concerns the industrial production index. It would be logical to use the index that includes construction. But the results presented in this paper are obtained using the index excluding construction, because real-time data are only available for this index. Furthermore, even if real time data had been available for total IPI, it would have been probably difficult to use them, due to the substantial revision of total IPI in the last quarter of 2007[3].

[1] All used in previous work on GDP estimate.
[2] All PC embed all individual series.
[3] Between the November and December 2007 releases.

Since this recent change (see figure 2), the econometric results (i.e. the fit) with the most recent GDP data are improved with the series including construction.

Figure 1: Changes in the retail confidence indicator (*)

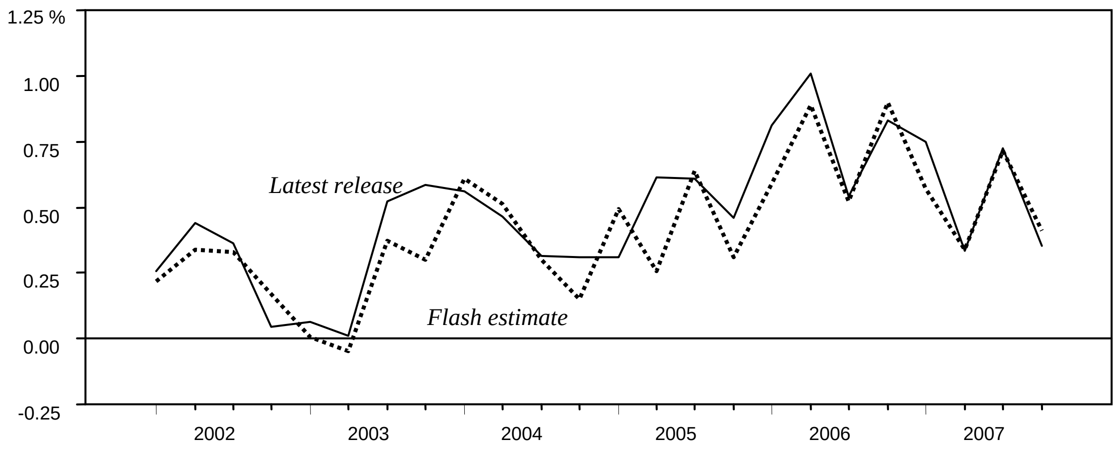


(*) The series is plotted in a quarterly frequency i.e. that of our models

Figure 2: Changes in the industrial production growth rates (*)

(*) Including construction ; in quarterly frequency.

Figure 3: Quarterly GDP growth rates, latest release (solid line) and flash estimate (dotted line)



All these revisions, together with GDP revisions (Figure 3 shows the revisions between the flash estimate growth rates and the latest release), lead us to conclude that it is impossible to choose just one model and stick to it forever. Starting from the above consideration, we have adopted a strategy of regularly re-assessing all the models in order to choose the better performing one at each step.

4. Two regression models for GDP with individual series

In this section we will present the first two models used in our simulation exercise. The main difference between the two models is that the first one includes the IPI as regressor while the second one doe not. The second model is built to answer the question: can we estimate GDP without using IPI? From a theoretical point of view, introducing IPI is a good option because it is a good proxy of gross value added in the industry, which is still a relevant component of GDP and is used by many euro area countries to produce their flash estimates. But in practice this generates two difficulties: industrial production is subject to rather long publication delays (industrial production for month (m–2) is released at mid-month m) and to substantial revisions. The delay implies that it is necessary to forecast IPI[4] and IPI revisions lead to some variability in GDP estimates. In the second model, IPI is replaced by the industrial confidence index because it is the main series relevant to forecast IPI and it is usually not subject to revisions.

Aside from these coincident series, the two models include the same leading regressors (see Table 1), namely the confidence index of the construction survey, the households' opinion on major purchases and only one leading financial series, the real euro-dollar exchange rate[5]. Finally, except for IPI, all regressors are taken among survey data and financial data. These series have the advantage of being released more rapidly than IPI and are generally not subject to revisions[6].

Table 1: Coincident and leading series used in the two models

Regressors	Lag
GDP1 : Industrial production index(*) (growth rate) GDP2 : Change in industrial confidence index	0
Change in households’ opinion on major purchases over next 12 months	1
Change in construction confidence index	3 and 4
Real dollar/euro exchange rate (growth rate)	2

(*) Excluding construction

At the release date of a coincident GDP indicator for quarter T, industrial production data covers possibly two, one or no months of this quarter. It is thus necessary to forecast industrial production for the missing months, which will be done with a regression model described in section 6. On the other hand, when survey data are used, one month of survey data is missing for the first GDP estimate. For the other two months, survey data are entirely

[4] Unfortunately, IPI forecasts are not very accurate due to the high volatility of the series.
[5] Interest rate variables are excluded for the reason given in Section 3.
[6] If we except exceptional revisions, like those mentioned in Section 3.

available for the quarter to be estimated. When one month of survey data is missing, we use the average of the two available months to replace the average of the three. Two other variables could have been considered, as they appear sometimes significant in the 72 past regressions, i.e. the lagged real oil price growth rate and the sales' growth rate. But the latter is coincident, released with delay and available only from 1995. Thus, introducing sales raises too many problems. We have left the two series out of the regression and we will see in the future if their introduction could be relevant.

We now turn to the out-of-sample estimation errors done with these two models using real-time data, over the last six years (2002-2007). For example, the GDP of the first quarter 2002 is obtained with data available at the end of year 2001 and at the beginning of 2002 (end of January) etc… until the GDP of the fourth quarter 2007, obtained with data available at the end of year 2007 and at the beginning of 2008 (end of January). Thus 72 regressions per model are run. All estimation errors are computed with the GDP flash estimate growth rates.

The GDP1 model explains at least 79% and at most 84% of the variability of GDP growth rate; the GDP2 model, at least 72% and at most 76%.We first test the unbiasness of our estimations. For that, the following regression can be run:

$$y_{t+1} = a + b\,\hat{y}_{t+1,t} + \eta_{t+1}$$

where y_{t+1} is the flash estimate growth rate in (t+1) and $\hat{y}_{t+1,t}$ the estimation made in t for (t+1) and one can check whether {a = 0, b = 1}. Table 2 gives the p-values of this test. The GDP1 model gives unbiased estimates; we cannot be so affirmative for the GDP2 model.

Table 2: P-values of the unbiasness test

Estimation dates of the GDP of quarter *T*	GDP1 model	GDP2 model
End of month 2 of quarter *T*	8 %	3 %
End of month 3 of quarter *T*	50 %	3 %
End of month 1 of quarter (*T*+1)	12 %	3 %

Table 3 shows the RMSE of each model run with real time data over 2002Q1-2007Q4. Table 3 also shows the RMSE associated with the combined estimates[7] and of an AR(1) model.

Table 3: Root mean squared errors (in percentage point) using real time data over 2002Q1-2007Q4 according to the estimation dates

Estimation dates of the GDP of quarter *T*	GDP1 model	GDP2 model	Combining the two models	AR(1) model
End of month 2 of quarter *T*	0.20	0.22	0.20	0.23
End of month 3 of quarter *T*	0.17	0.22	0.18	0.23
End of month 1 of quarter (*T*+1)	0.18	0.22	0.18	0.23

[7] Average of the estimates.

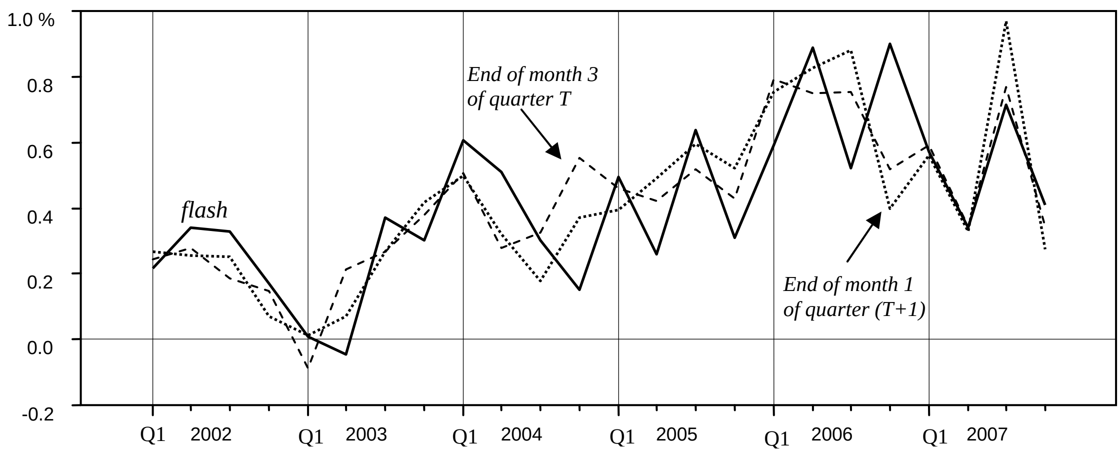
Table 3 suggests that the GDP1 model (with IPI) performs better than the GDP2 model, and that the AR(1) model is the worst. The GDP2 model has less accurate estimates, but these estimates do not change according to the estimation date, contrary to the GDP1 model whose estimates are rather volatile. However, are the RMSE shown in Table 3 significantly different? To answer this question we perform several Diebold-Mariano tests and show their p-values in Table 4.

The null hypothesis of the test is given in line 1, the alternative and the p-value, in each box of Table 4. When the two models GDP1 and GDP2 are compared, the null hypothesis is rejected only once (p-value=2%). Thus, with this criterion and six years of real-time data, it appears that including IPI in the model improves the estimation only for the intermediate estimation date. Curiously the GDP1 estimation is less accurate at the most favourable date (last line of Table 4), when there is only one month missing for IPI. This result is due to three poor estimations namely in 2006 Q3, in 2006 Q4 and in 2007 Q3 (see Figure 4). For the first two dates, the forecast error of the missing month of IPI is particularly high, higher than that made when two months of IPI are missing. For the third date (2007 Q3) the same estimation error would appear with no missing month for IPI. Combining the two estimates does not improve the performance of the model as could be thought from the RMSE (see Table 3). When the GDP2 and AR(1) models are compared, the null hypothesis is never rejected[8]. Thus, the GDP2 model is not better than an AR(1).

Table 4: P-values of the Diebold-Mariano test performed between the two models according to the release date.

Estimation dates of the GDP of quarter *T*	H0 GDP1=GDP2	H0 GDP1=COMBIN
End of month 2 of quarter *T*	GDP1>GDP2 9%	GDP1>COMBIN 29%
End of month 3 of quarter *T*	GDP1>GDP2 2%	GDP1>COMBIN 11%
End of month 1 of quarter (*T*+1)	GDP1>GDP2 15%	GDP1>COMBIN 55%

Figure 4: Quarterly GDP growth rates
flash estimates (solid line) and GDP1 estimates (dotted line), according to the release date



[8] P-values are not reproduced in Table 3.

5. Principal component regression for GDP growth rates

In order to extract principal components, we consider a small data set including variables that appeared significant in our three previous regression models (see [3]) except for the retail confidence index and the interest rate spread, which are not considered for the reasons given in section 3. Table 5 shows the selected series.

Table 5: Coincident and leading series used to construct PC

Series	Lag
Industrial production index (exc. construction) (growth rate)	0
Change in industrial confidence index	0
Households' financial situation over next 12 months	0
Change in households' opinion on major purchases over next 12 months	1
Change in construction confidence index	3 and 4
Change in employment expectations in construction	3 and 4
Real dollar/euro exchange rate (growth rate)	2

If these series played with a lag in our previous models, they are also lagged in the data set (lags are given in Table 5). All in all, this gives us nine series. As they cannot be used simultaneously in a regression because of their collinearity, we extract the PC of the data set. This is a way of keeping all these individual series directly related to GDP growth rate. The extraction of PC is carried out on standardized data, i.e. we compute the eigen vectors and values of the correlation matrix. We then regress the GDP growth rate on these nine PC and a constant term. We finally select the significant PC.

Since we run a real-time analysis, we perform 72 principal component analyses and 72 regressions. All regressions include the first three factors[9], none of them includes the sixth, eighth and ninth factors[10]. On average, four or five PC are present in the 72 regressions. Let us note that this method does not give better fits than a regression with individual series. However, for out-of-sample estimations, this could be better even if the in-sample estimation is not. Its potential superiority derives from being estimation less dependent on extreme changes of regressors. In Table 6, the RMSE of the estimations are reported as well as the p-values of the test of absence of bias and of the Diebold-Mariano test. The absence of bias is verified.

Table 6: Root Mean Squared Error and P-value of tests using real time data over 2002Q1-2007Q4 according to the estimation dates

Estim. dates of the GDP (quart. *T*)	RMSE	P-value {H0=no bias}	P-value { H0 : PC-model = GDP1}
End of month 2 of quarter *T*	0.17	33 %	PC-model > GDP1 0 %
End of month 3 of quarter *T*	0.15	77 %	PC-model > GDP1 6 %
End of month 1 of quarter (*T*+1)	0.16	43 %	PC-model > GDP1 7 %

Even if the Diebold-Mariano test does not conclude to the superiority of this PC-regression model for two out of three estimation dates (at the significance level of 5%), Table 6 leads us

[9] The PC are ranked according to the % of inertia they explain.

[10] For the PC that represent a small part of inertia, nothing certifies *a priori* that the sixth PC in one PCA correspond to the sixth in another one.

to conclude that this model is currently the better performing one. Figure 5 plots the real-time estimations according to the release date.

Figure 5: The quarterly GDP growth rates flash estimates (full line) and GDP estimates with PC-model (dotted line), according to the release date

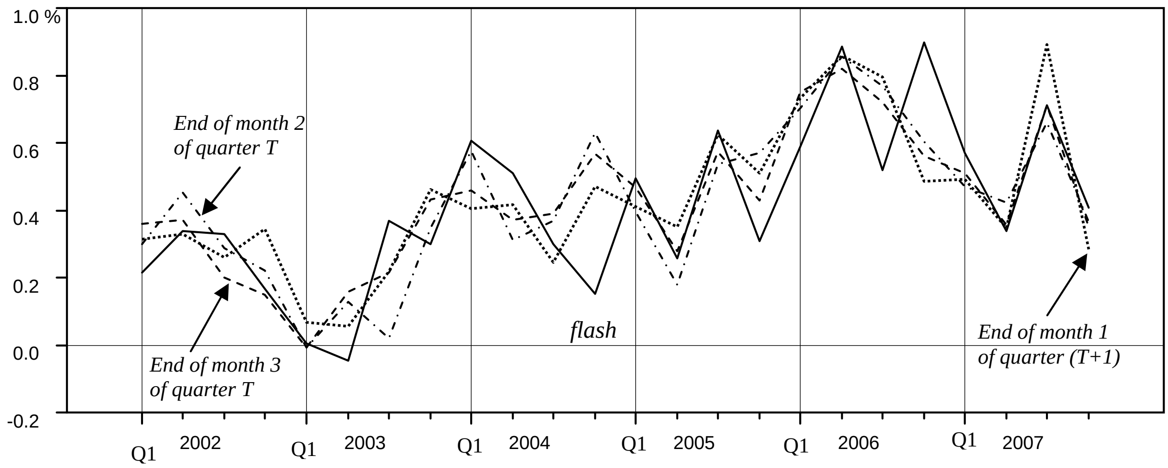


Figure 6 plots the real-time estimations given by the GDP1 model and by the PC-regression model for the estimation date where the performance results the best (end of month 3 of quarter *T*).

Figure 6: The quarterly GDP growth rates flash estimates (full line), GDP1 estimates and PC-model estimates (dotted line), for the intermediate release date

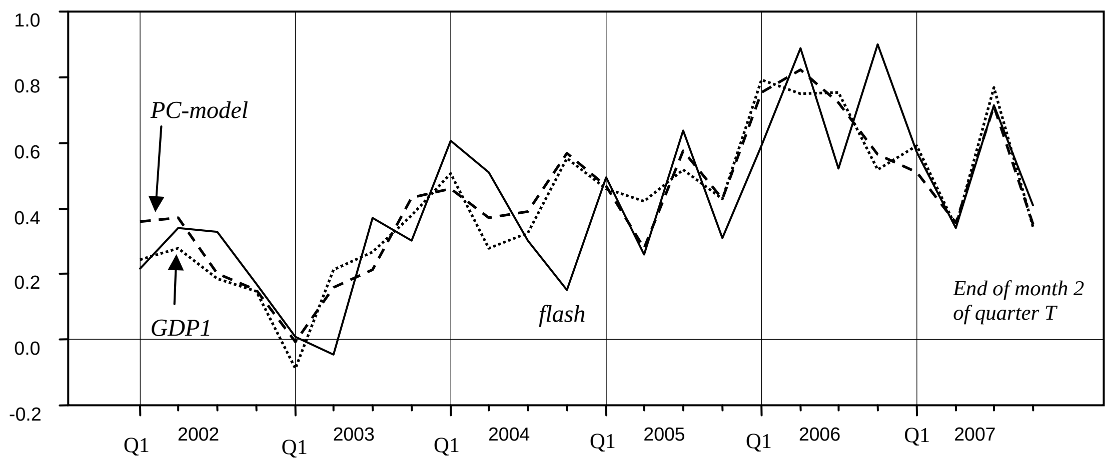


Figure 6 shows that the biggest estimation errors are in 2004 Q4 and 2006 Q4. For the PC-regression model, all other errors are small. The two major estimation errors are probably accentuated by the method used to produce the flash estimate of the fourth quarter[11]. These errors are a bit lower with revised data but they still remain high. Nevertheless we have to admit that this is far from being the only source of error.

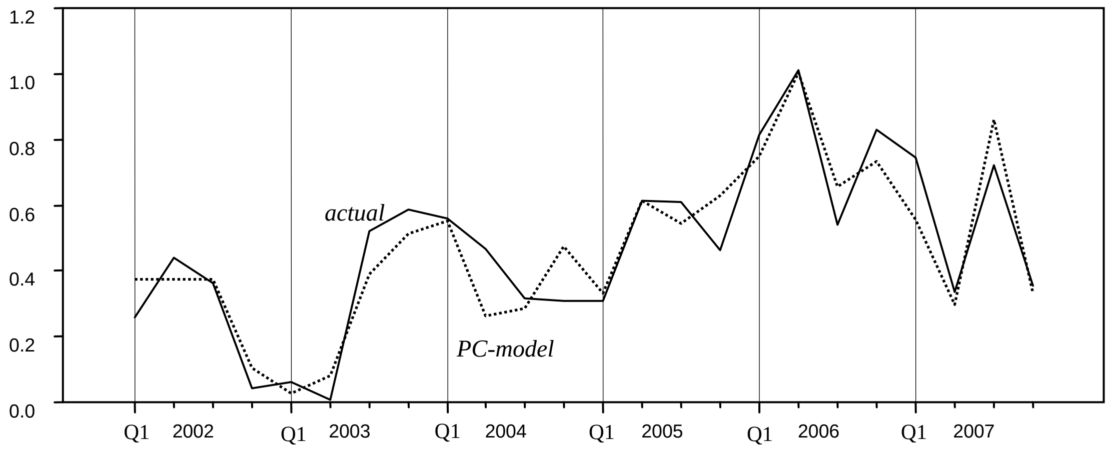
If we now carry out an in-sample analysis with the most recent data and with industrial production including construction, the fit on the estimation period (2002-2007) shows that

[11] When data are not available for some countries at the release date of the official estimate for the fourth quarter, latest official annual forecasts produced by the DG-ECFIN may be used as a benchmark.

2006 Q4 error is not so large. The error of 2004 Q4 is lower but remains and does not depend on the IPI used.

Finally, we can ask the following question: what is the best performance that may be reached with data and models we chose to use? To answer this question, we carry out out-of-sample estimations over 2002-2007 using the latest GDP release, the latest releases of individual series and we assume that coincident series are entirely available for the quarter we estimate. The most accurate results are those of the PC-model with industrial production including construction. The RMSE is then 0.10 percentage point only. Figure 7 compares actual GDP growth rates with these “ideal” estimates. Substantial errors remain in 2004Q2 and 2004Q4, 2005Q4 and 2007Q1. Choosing the current sample of IPI including constructing rather than IPI excluding construction improves noticeably estimates for 2005Q2, 2006Q4 and improves also slightly estimates for 2002Q2, 2002Q4 and 2004Q4.

Figure 7: The actual quarterly GDP growth rates (full line), and PC-model estimates (dotted line), with IPI including construction



6. Real time analysis of IPI models

We have developed several equations for industrial production (see [2] and [3]). For the purpose of the examination of real-time estimates, we have run the exercise on the basis of one of our preferred equations.

We had chosen initially to produce estimates for total industry production because we intended to use it in our GDP estimate. However, the main variable of the EUROSTAT monthly industrial production *news release* is industrial production excluding construction (which will be referred to thereafter as IPIX).

Total industrial production (IPI) and IPIX did not have until recently too different growth rates, although IPIX exhibited clearly less volatile monthly fluctuations than the broader index. This was true until the November release embedding data up to September 2007. The December industrial production release with data up to October 2007 shows a strong revision[12] of total industrial production all over the period under review (i.e. since 1990m4, see Figure 8a), with the most volatile fluctuations in terms of monthly growth rates having been strongly reduced and brought in line with those of industrial production excluding construction (see Figure 8b), in particular for the periods: 1997m4-m5 - 2005m4-m5.

---

[12] As already mentioned in section 3.

Figure 8a: Euro-zone total IPI monthly growth rates,
as in November and December 2007 releases: a substantial revision

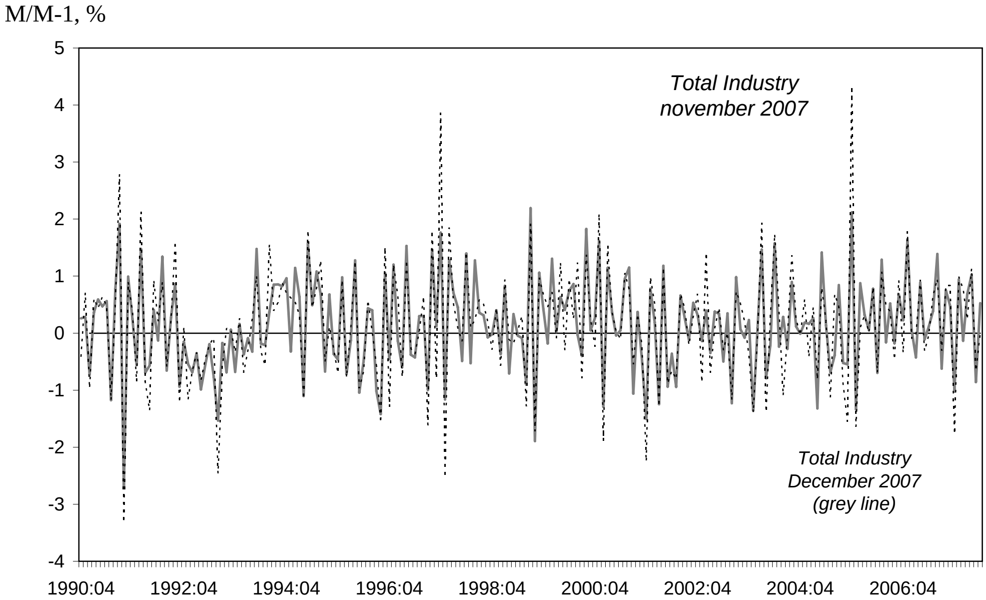
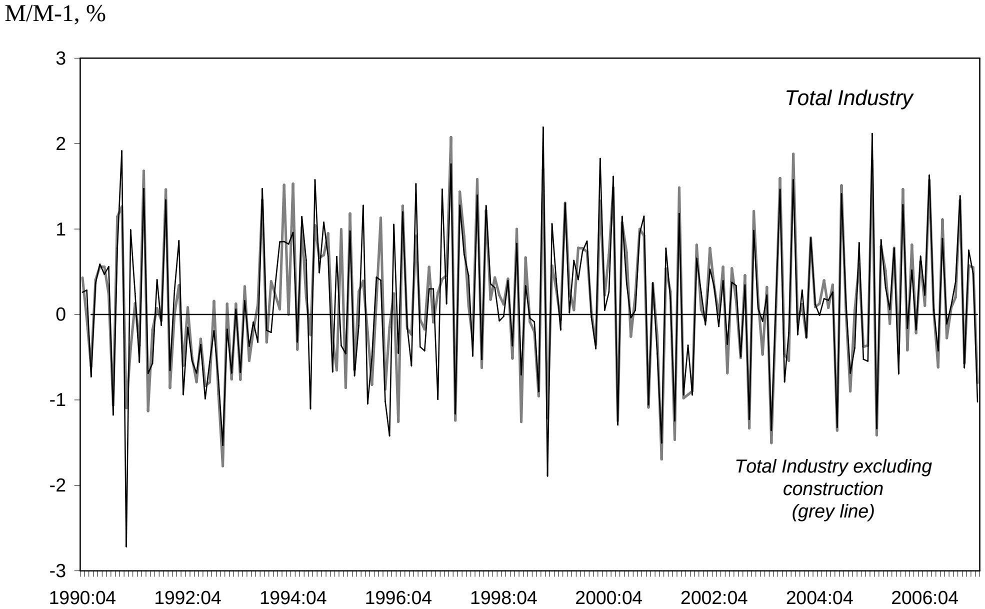


Figure 8b: Euro-zone total IPI and total IPI excluding construction monthly growth rates,
as in December 2007 release



Source: EUROSTAT

Table 7 shows the explanatory variables in our reference equation for total IPI. The equation is used to estimate industrial production growth one month-ahead. The equation includes past industrial production monthly growth rates, with one and two lags. The euro real effective exchange rate (as estimated by the IMF on the basis of unit labour costs in the manufacturing industry) plays with a 3-month lag. The industrial confidence index is taken from the DG-ECFIN business and consumer survey results. It plays both in variations (coincident and one lag) and in level (coincident). All regressors have a straight link with activity in the industrial sector.

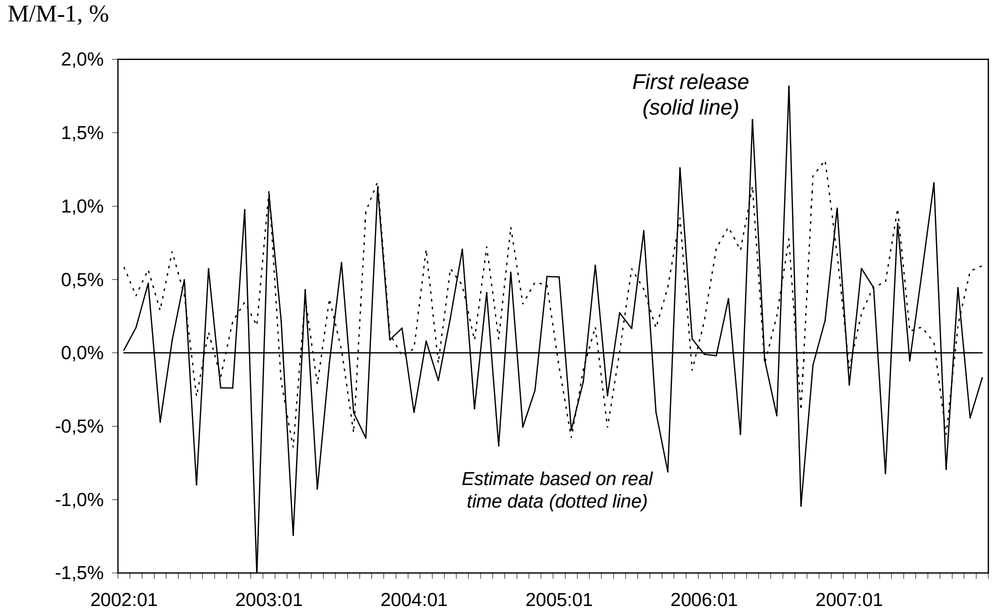
Table 7: Coincident and leading variables entering the equation giving monthly industrial production growth rate

	Lag
Monthly industrial production growth rate (%)	1
Monthly industrial production growth rate (%)	2
Real effective exchange rate growth rate (%)	3
Change in industrial confidence index (first difference)	0
Change in industrial confidence index (first difference)	1
Industrial confidence index	0

All variables entering the equation have coefficients significantly different from 0, with the expected sign. The coefficients are broadly unchanged as compared to the estimate run until 2007m12, although the mentioned above substantial revision in IPI data released in December lowers significantly the SEE to 0.6 percentage point instead of 0.8 before.

For data before the beginning of the regular production of our monthly production indicators, we use the real-time backup of the EuroInd database on the day of the industrial production *news release*: hence IPIX and industrial confidence are in real-time. The real effective exchange rate is taken from the IMF database, which we do not have in real-time. For the purpose of this exercise, we will consider that this variable is not revised over time. This seems plausible – at least in view of the dataset we have stored since starting monthly estimates of the indicator in September 2006 - but would remain to be checked over a longer period of time. Figure 9 shows the first release of IPIX data and the estimate based on real-time data from 2002.

Figure 9: Monthly growth rates: first releases and real time estimates over 2002m1-2007m12, one-month ahead, equation 2, IPI excluding industrial construction



Unfortunately, we can't consider that this estimate is unbiased, the p-value of the test being equal to 1%. Does our model perform better than an autoregressive one? In the case of IPIX, the best autoregressive model is found to be an AR(4). The out-of-sample forecast errors over (2002m1-2007m12) with real time data have an RMSE equals 0.62 percentage point. For the AR(4) model we find 0.62 too (see Table 8). The Diebold-Mariano test accepts the assumption that the two RMSE are equal (p-value=54%).

Table 8: RMSE and P-values of the Diebold-Mariano tests for monthly IPIX growth rates, 2002m1-2007m12

In percentage point

Type of errors	RMSE	P-value of Diebold-Mariano test $M_i = M_j$ versus $M_i < M_j$
M1: Out-of-sample errors (equation re-estimated each month, real time data)	M1 = 0.622	M1=M2 vs M1<M2 54%
M2: Out-of-sample errors with an AR(4) model re-estimated each month, real time data.	M2 = 0.617	M2=M3 vs M2<M3 7%
M3: Combined estimate M1 and M2	M3 = 0.585	M1=M3 vs M1<M3 8%

However, we could think of combining the results of equation 2 and the AR(4), through a simple arithmetic average of the two forecasts. The P-value of the Diebold-Mariano test then comes down to 8%, which may suggest that combining our model with an AR(4) model could give better results. Let us note that the combination can be considered as unbiased (P-value equal to 13%)

7. Conclusions

The results obtained in the paper appear to be encouraging especially for euro area GDP while the model for industrial production still needs some improvements due to the high volatility of the variable.

Industrial production appears to be necessary to produce GDP growth rate coincident estimates independently by the chosen approach: regressions with individual series or with principal components. Now that industrial production including construction has been completely revised, the question is whether this series really outperforms IPI excluding construction in estimating GDP. Our first investigation allows us to answer positively, but this question will be re-examined in the future. The last conclusion of our real-time analysis is that the PC-model performs slightly better than a regression embedding individual series as regressors.

The frequent revisions of euro area data sets means that it is necessary to re-consider regularly the list of individual series entering models that provide estimates. Until now the accuracy of our estimates is far from being perfect. Even in ideal conditions in terms of data availability, the accuracy can be considered as insufficient. Future improvement could come from more accurate IPI forecasts, new series in the data set and, perhaps also, an approach per country.

References

[1] Boivin, J., and S. Ng, 2006, ‘Are more data always better for factor analysis?’, *Journal of Econometrics*, vol 132, issue 1, May, 169-194.

[2] Charpin F. and Mathieu C. (2007): ‘Compilation, supervision and quality assessment process of coincident indicators for some Euro-zone PEEIs’, *Lot 3: Principal European Economic Indicators (“PEEIs”) statistical production and analysis, Task 6, EUROSTAT project*, January.

[3] Charpin F. and Mathieu C. (2007): ‘Compilation, supervision and quality assessment process of coincident indicators for some Euro-zone PEEIs’, *Lot 3: Principal European Economic Indicators (“PEEIs”) statistical production and analysis, Task 6, EUROSTAT project*, December.

[4] Stock, J.H., and M.W. Watson, 2002, ‘Forecasting Using Principal Components from a Large Number of Predictors’, *Journal of the American Statistical Association*, 97, 1167-1179.

Annex 1

Table A1 lists the 21 series from the data set used to extract principal components. Survey data series are considered both in level and in first difference. For financial data, we use the following transformations: the change in the three-month interest rate, the change in the ten-year government bond interest rate, the spread between these two interest rates, the growth rate of the real euro-zone stock market, the growth rate of the real dollar-euro exchange rate, the growth rate of the real oil price. We extract factors using principal component analysis carried out on standardized data, i.e. that we compute the eigen vectors and values of the correlation matrix.

Table A1: The data set

```
INDUSTRIAL PRODUCTION INDEX EXCLUDING CONSTRUCTION
INDUSTRIAL SURVEY: CONFIDENCE INDEX
CONSUMER SURVEY: CONFIDENCE INDEX
CONSUMER SURVEY: MAJOR PURCH.OVER NEXT 12 MONTHS
CONSUMER SURVEY: FINANCIAL SITUATION NEXT 12 MTH.
CONSTRUCTION SURVEY: CONFIDENCE INDEX
CONSTRUCTION SURVEY: EMPLOYMENT EXPECTATIONS
RETAIL SURVEY: CONFIDENCE INDEX
EURO INTERBANK RATE - 3MONTH
10-YR BOND YIELD
INTEREST RATE SPREAD (10YR-3MTH)
REAL SHARE PRICES (MSCI, euro-zone)
REAL EXCHANGE RATE – U.S. $ TO EURO
REAL OILBREN PRICE
```

We then regress the GDP growth rate on these first ten PC current and lagged and on a constant term. We finally select the PC and their lags which are significant. Since we run a real-time analysis, we perform 72 component principal analyses and 72 regressions. Only the first eight PC are significant at least once in the 72 regressions. All regressions contain the first third PC, the third being lagged (2 quarters).

The RMSE of the estimation is equal to 0.20 percentage point whatever the estimation date (Table A2). The estimates are unbiased (Table A2). This model, named SW-model, is compared with our PC-model using the Diebold-Mariano test. It is clearly less good for two estimation dates (Table A2).

Table A2: Root Mean Squared Error and P-value of tests using real time data over 2002Q1-2007Q4 according to the estimation dates

Estim. dates of the GDP (quart. *T*)	RMSE	P-value {H0=no bias}	P-value { H0 : PC-model = SW-model }
End of month 2 of quarter *T*	0.20	14 %	PC-model > SW-model 12 %
End of month 3 of quarter *T*	0.20	18 %	PC-model > SW-model 0.6 %
End of month 1 of quarter (*T*+1)	0.20	12 %	PC-model > SW-model 3 %