Construction of coincident indicators for the euro area. 5th EUROSTAT Colloquium on Modern Tools For Business Cycle Analysis, Luxembourg, 29th September - 1st October 2008

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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. The paper also presents a new indicator for euro area employment quarterly growth, which seems to perform rather well in the recent past, although this is still a preliminary assessment as we are only at an early stage of running the indicator.

JEL classification code: E37

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

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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). These key variables for short-term economic analysis are part of the set of the 22 'Principal European Economic Indicators' selected by EUROSTAT[1]. They have been chosen essentially due to the late availability of first official estimates even if some remarkable improvements in terms of their timeliness have occurred in the last years. The comparison is made on the basis of real time results provided by these models over six years (2002-2007).

Section 2 provides a description of the methodologies we use. Section 3 addresses data problems we have met in the process of constructing our indicators. Real time analyses are carried out with our approaches for euro area GDP in Sections 4 and 5. Section 6 is devoted to a monthly IPI estimate. In Section 7 we present a new indicator for euro area employment quarterly growth. Section 8 concludes.

2. A regression-based methodology

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 ($T+1$). We compare several approaches based on regressions using either individual series or principal components as regressors. Principal component regressions have become very popular since Stock and Watson (2002).

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 raises 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 for industrial production in 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 we ran three regression models with individual regressors in order to produce each month three GDP estimates and then average them to provide a final GDP estimate (see Charpin and Mathieu 2007a, b). From this past experience, we have selected two regression models analysed in Section 4. We have also run principal component

[1] See 'An overview of the business cycle in the euro area and the European Union - A set of key indicators available daily on a single webpage', *news release,* 16 October 2007.

regressions but did not continue in that direction because we found that they did not perform better than traditional regression models with individual series (see Charpin and Mathieu 2007a). We had then carried out the usual method by Stock and Watson (2002). In this paper (see Annex 1) we use a real time data set and conclude again that this method can be discarded. Principal component regressions presented in Section 5 are carried out using a different method. Principal components (PC) are usually 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 Boivin and Ng, 2006]). Hence our suggestion is to consider only series directly related to GDP growth[2], in principle series that can help to predict GDP growth but cannot be introduced simultaneously in a regression because of multicollinearity. Moreover these series are lagged if they show 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[3], with their own either coincident or leading characteristics.

All results shown in this paper for GDP and IPI growth rates are derived 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 for a given quarter are run with data available at the time of producing the estimate. We have been able to carry out such a real time analysis thanks to the EUROSTAT EuroInd database backup. Thus, even if our models did not exist, it is possible to assess their performance within a real time simulation exercise.

3. Data problems and their consequences

In the process of estimating our different models, we faced several data problems. 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 run to estimate the first quarter of 2002 are based on a GDP series starting in the first quarter of 1995 and ending in the fourth quarter of 2001. It has thus been necessary to back-recalculate real GDP series, which we have done back to the first quarter of 1992, using old GDP series in 1995 prices. We have then checked that our selected regressors remained significant if we started the estimation in 1995Q2 in order to make sure that our back-recalculation did not introduce false signals. Through this checking process, we were led to exclude interest rate variables from our models. These variables were either the variation of the short-term interest rate with a two-quarter lag or the spread of interest rates (10 year minus 3 month) with two or three quarter lags, depending on the model. We observed that all interest rate variables were no more significant when we ran our models starting from the first quarter of 1993 and later, instead of 1992Q2.

The second data problem comes from the retail trade survey (released by the DG-ECFIN). Generally survey data are not revised except for the latest observations. In reality, survey data series have been subject to several revisions with the most substantial one affecting the retail trade survey between the October and November 2006 releases (see Figure 1). We could observe that the degree of significance of the retail trade confidence indicator fluctuated in our models according to the estimation period, which is not surprising given the size of the

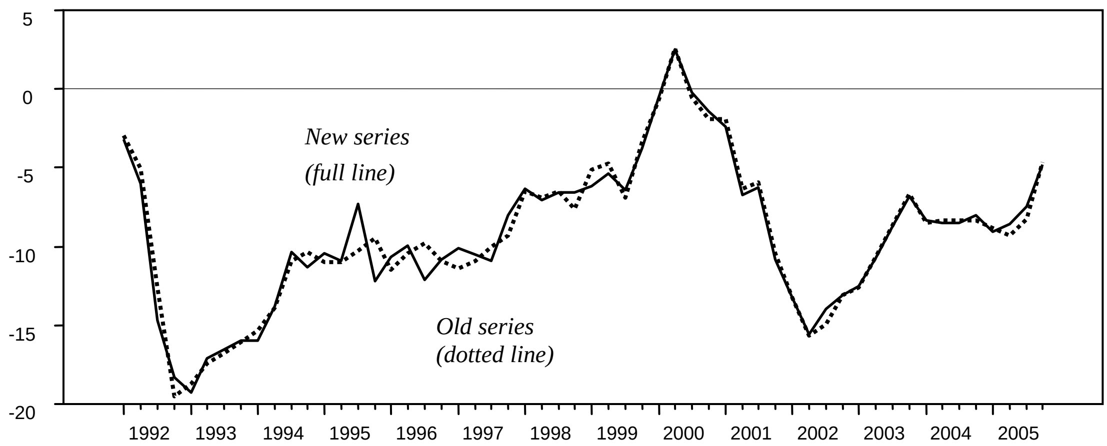
[2] All used in our previous work on GDP estimates.
[3] All PC embed all individual series.

revisions. Hence we chose to leave this survey out of our estimates because it did not seem fully reliable.

The third data problem concerns industrial production. It would be logical to use the total industrial production index to estimate GDP. But the results presented in this paper are obtained using the index excluding construction, the only one for which real time data are only available. Besides, even if real time data had been available for total IPI, it would have been probably difficult to use them in view of the substantial revision of total IPI in the last quarter of 2007 (more precisely between the November and December 2007 releases).

Since this recent revision (see Figure 2), using the index including construction improves the econometric results (i.e. the fit) obtained with the most recent GDP data.

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

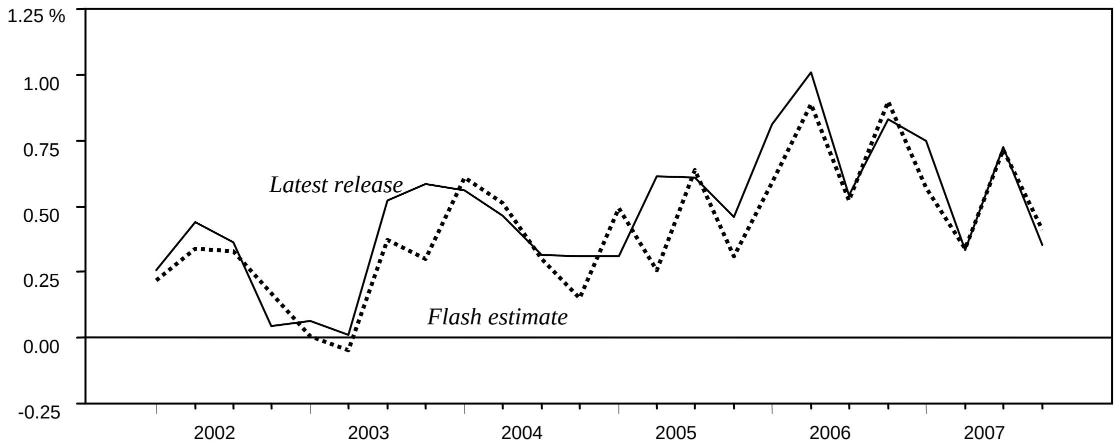


(*) The series is plotted in a quarterly frequency i.e. the frequency of our GDP indicators

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 ones (Figure 3 shows the revisions between the flash estimate and the latest release), lead us to conclude that it is impossible to choose a single model and stick to it forever. This is why we have adopted a strategy of regularly re-assessing our models in order to choose the better performing one at each point.

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 IPI as a regressor whereas the second one does 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. This delay implies that IPI needs to be forecast[4] and IPI revisions also lead to some variability in GDP estimates. In the second model, IPI is replaced by the industrial confidence indicator because it is the main series relevant to forecast IPI and it is usually not subject to revisions.

Apart from these coincident series, the two models include the same leading regressors (see Table 1), namely the construction confidence indicator, households' opinion on major purchases over next 12 months and only one financial series - the real euro-dollar exchange rate[5]. Finally, except for IPI, all regressors are 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].

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[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.

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

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

(*) Excluding construction

At the time of producing a coincident GDP indicator for quarter *T*, industrial production data are available for 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 using a regression model described in Section 6. As concerns survey data, only the figure for the last month of the quarter is not available at the time of producing the first GDP estimate for the considered quarter. Survey data are entirely available for the following GDP estimates of that quarter. When one month of survey data is missing, we use the average of the two available months as an estimate of the quarter. Two other variables sometimes appear significant in our real-time 72 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 would raise too many problems. We have left the two series out of the regression and we will re-examine in the future if their introduction could be relevant.

Let us turn now to the out-of-sample estimation errors of our two models using real time data over the last six years (2002-2007). We start and estimate GDP growth for the first quarter 2002 using data available at the end of 2001 and at the beginning of 2002 (end of January) and so on… and finally estimate GDP growth of the fourth quarter 2007 with data available at the end of year 2007 and at the beginning of 2008 (end of January). Thus 72 regressions are run for each model. 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 the GDP growth rate; the GDP2 model, at least 72% and at most 76%.We first test the unbiasness of our estimations. For that purpose, 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 shows 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 for GDP growth 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 with 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 for GDP growth 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

Table 3 suggests that the GDP1 model (with IPI) performs better than the GDP2 model, and that the AR(1) model is the poorest. 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 run 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 GDP1 and GDP2 models 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 estimate only for the intermediate estimation date. Curiously the GDP1 estimate is less accurate at the most favourable date (last line of Table 4), when there is only one month missing for IPI. This is due to three poor estimates in: 2006Q3, in 2006Q4 and in 2007Q3 (see Figure 4). For the first two dates, the forecast error of the missing month for IPI is particularly high, higher than the error 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 does not perform better than an AR(1).

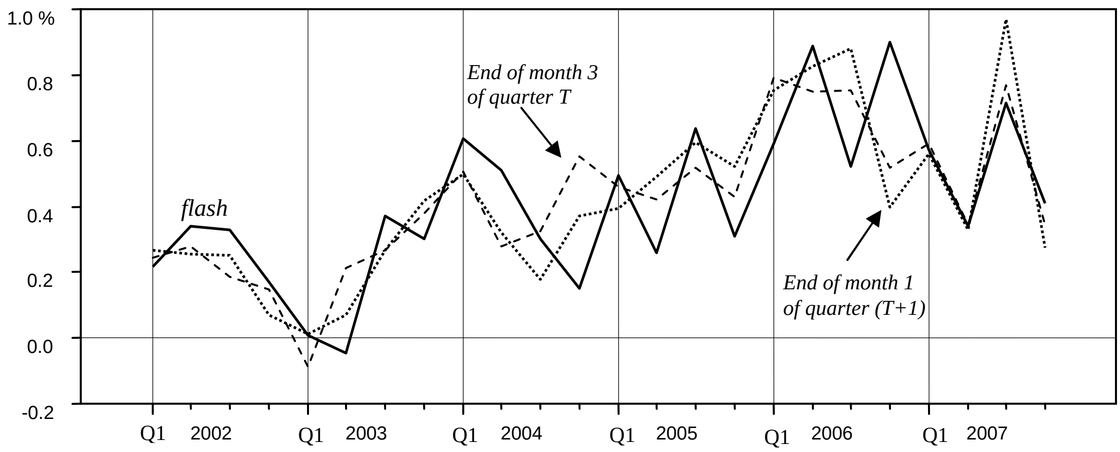
Table 4: P-values of the Diebold-Mariano test performed between the two models according to the release date.

Estimation dates for GDP growth, 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%

[7] Average of the estimates.

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

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



5. Principal component regression for GDP growth rates

In order to extract principal components, we consider a small data set embedding the variables that appeared significant in our previous three regression models (see Charpin and Mathieu, 2007b), except for the retail trade confidence indicator and the interest rate spread, which are not taken into account 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 indicator	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 indicator	3 and 4
Change in employment expectations in construction	3 and 4
Real dollar/euro exchange rate (growth rate)	2

When these series played with a lag in our previous models, they are also lagged in the data set (lags are shown in Table 5). All in all, this brings to consider 9 series. As these series 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 rates. 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.

We run a real-time analysis and so we perform 72 principal component analyses and 72 regressions. All regressions include the first three factors[9], no regression includes the sixth,

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

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. Table 6 shows the RMSE of the estimations and 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 to conclude that this model is currently the best performing one. Figure 5 plots the real-time estimates 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

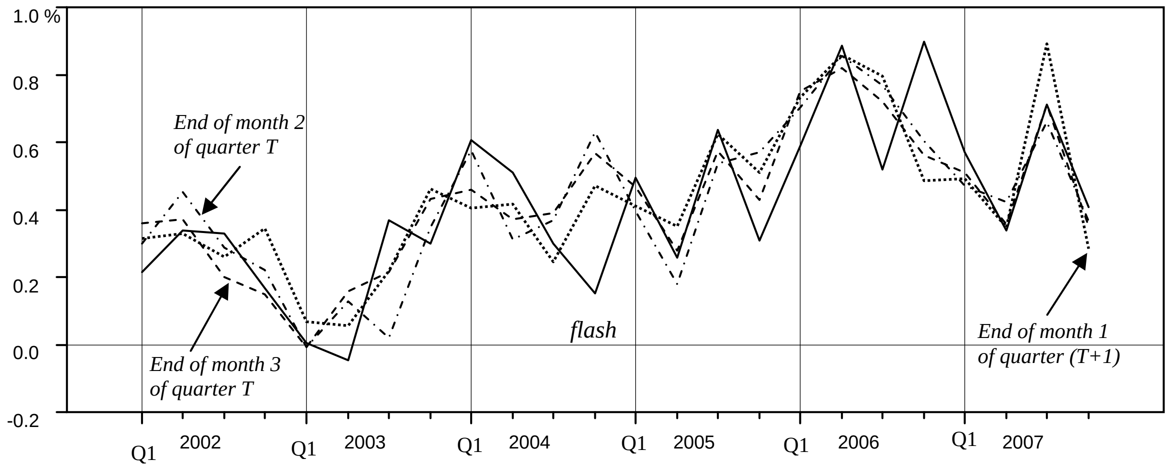


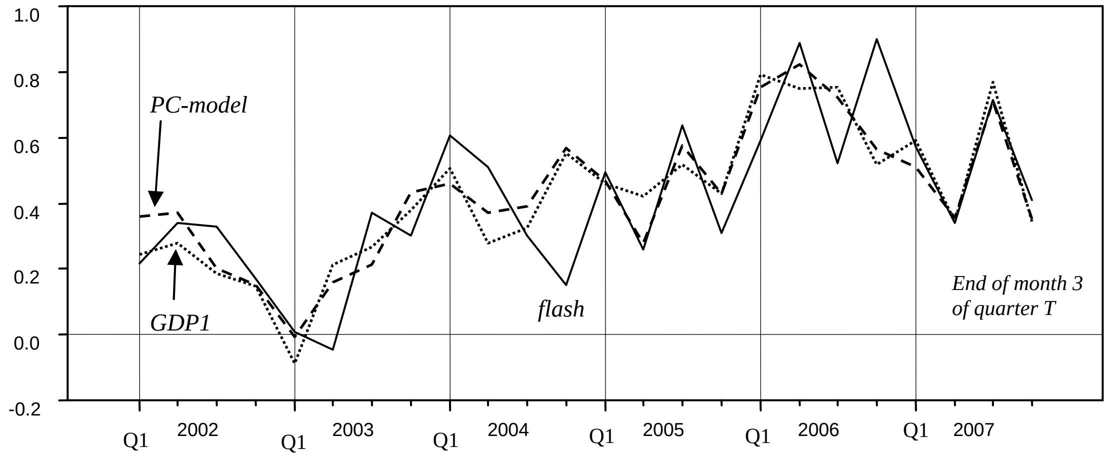
Figure 6 plots the real-time estimates produced by the GDP1 model and by the PC-regression model for the estimation date when the performance is the best (end of month 3 of quarter *T*).

Figure 6 shows that the biggest errors are produced 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.

[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.

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

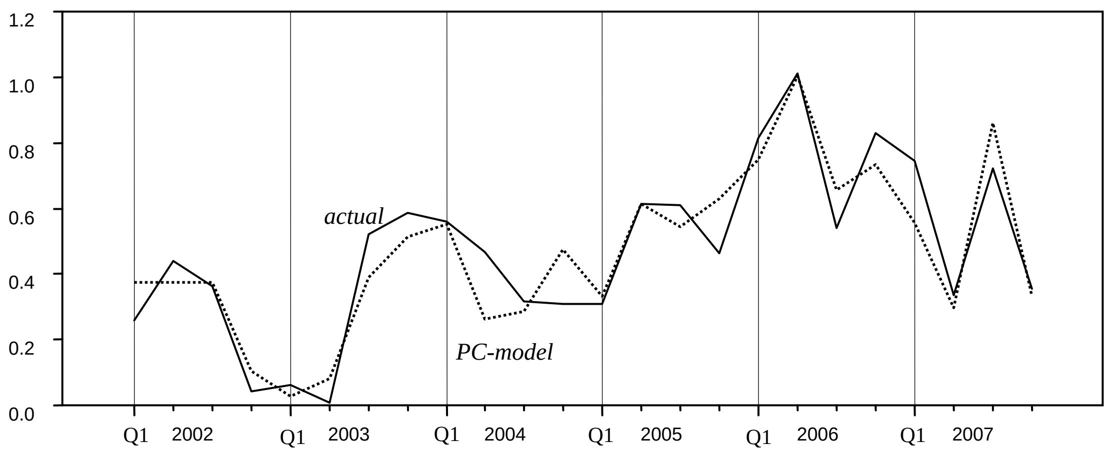
Figure 6: The quarterly GDP growth rates flash estimates (full line), GDP1 estimates and PC-model estimates (dotted line), for the intermediate release date



If we now carry out an in-sample analysis based on the most recent data and using industrial production including construction, the fit on the estimation period (2002-2007) shows that 2006 Q4 error is not so large. The 2004 Q4 error is lower but remains and does not depend on the IPI used.

Finally, we may ask the following question: what is the best performance we can expect from data and our selected models? In order to answer this question, we carry out out-of-sample estimations over 2002-2007 using the latest releases for GDP and 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, with a RMSE of 0.10 percentage point only. Figure 7 compares actual GDP growth rates with these "ideal" estimates. Errors remain substantial 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



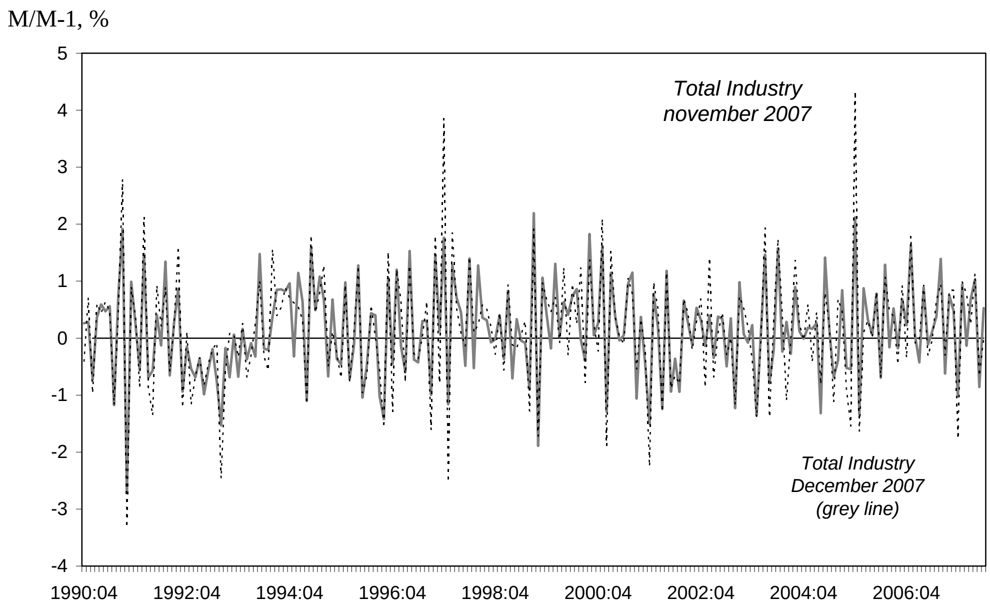
6. Real time analysis of IPI models

We have developed several equations for industrial production (see Charpin and Mathieu 2007a, b). 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 industrial 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.

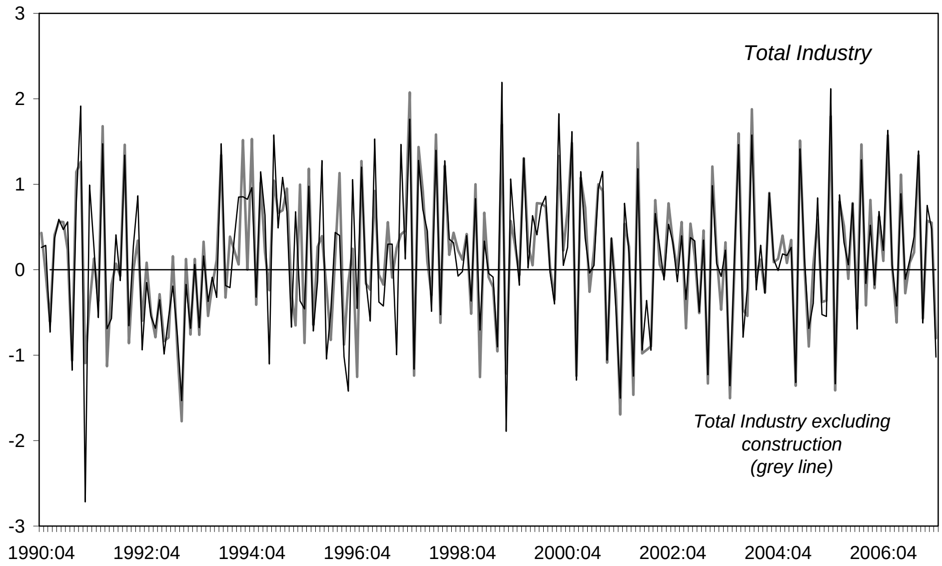
Figure 8a: Euro area total IPI monthly growth rates,
as in November and December 2007 releases: a substantial revision



[12] As already mentioned in Section 3.

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

M/M-1, %



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.

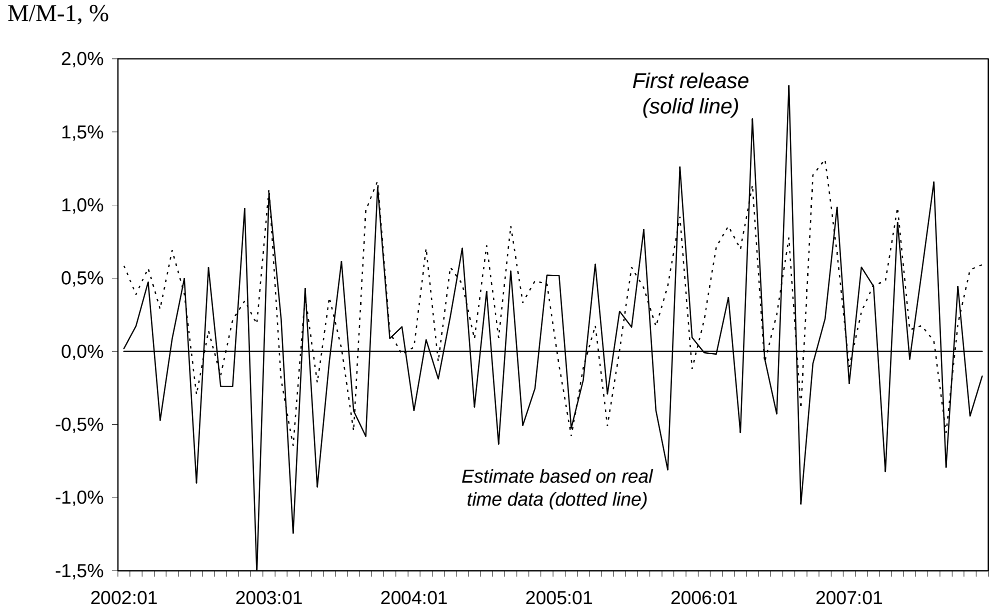
Table 7: Coincident and leading variables entering the equation giving monthly industrial production growth rate

	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 data set 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 cannot 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. A coincident indicator for euro area employment growth

Eurostat currently releases a first quarterly estimate of employment in national accounts 75 days after the end of the reference quarter and a second estimate 30 days later at the time of the second GDP release.[13] Employment is a closely watched variable and is – like GDP and IPI – one of the 22 Principal European Economic Indicators selected by EUROSTAT.

7.2 A new indicator

We have constructed an indicator for euro area employment quarterly growth and run it on a regular basis since early 2008. Our first estimate for the first quarter of 2008 was produced just after the official release of employment growth for the last quarter of 2007 (i.e. on 17 March 2008). We ran a second estimate for the first quarter of 2008 just after the EC Business and Consumer Survey release for March 2008 (31 March), and a third and last estimate for that quarter soon after the second employment release (9 April). In May, no new EUROSTAT figure for employment was to be released and we had only limited information at that stage for the second quarter (only one month for survey data) and so we did not run the employment indicator. We ran the first estimate for the first quarter of the year at mid-June (13 June) when a first official employment figure for the first quarter is released by EUROSTAT. We thus produce three estimates in a row for employment growth of a given quarter.

Like GDP, the euro area (EA-15) series for employment currently starts from 1995. We have back recalculated the series using the Euro area (EA-12) employment series back to 1992Q1, in order to be able to run our equation over a longer time period. We have checked that the equation run from 1992Q2 and the equation run from 1995Q2 give similar results.

Table 9: Coincident and leading variables entering the euro area employment quarterly growth rate equation

	Lag
Change in industrial confidence indicator (first difference)	0
Change in retail trade confidence indicator (first difference)	0
Change in construction confidence indicator (first difference)	1
Change in construction confidence indicator (first difference)	2
Employment expectations, manufacturing industry	2
Constant	

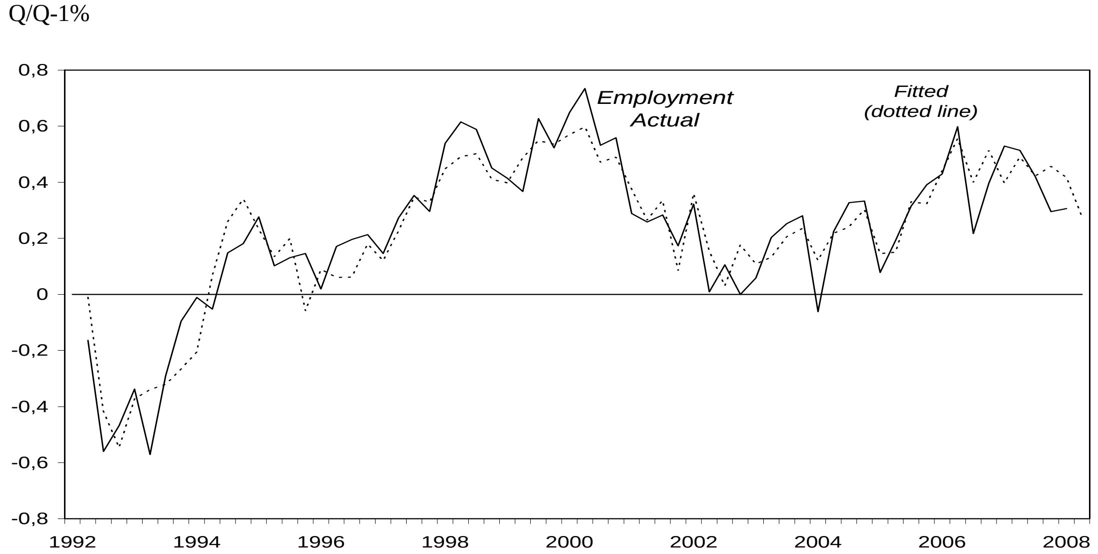
Table 9 shows the variables entering the equation for the employment quarterly growth rate. Employment growth seems best related with a bunch of EC-DG ECFIN business survey data covering three main sectors of the economy: industry, retail trade and construction. All survey data variables play in first difference. Industrial confidence and retail trade confidence are coincident with employment growth, while construction confidence plays with both a one and a two quarter lag. This means that one month of industrial and retail trade confidence will need to be forecast when we run our first employment for a given quarter. This forecast is done through a simple arithmetic average of the first two months of the quarter. We have also tested for the inclusion of specific questions on employment in survey data: only employment

[13] There is no specific employment *News Release* at that date

expectations in the manufacturing industry play a role, with a two-quarter lag. Employment expectations in the other sectors and unemployment expectations in the consumers' survey do not play a role.

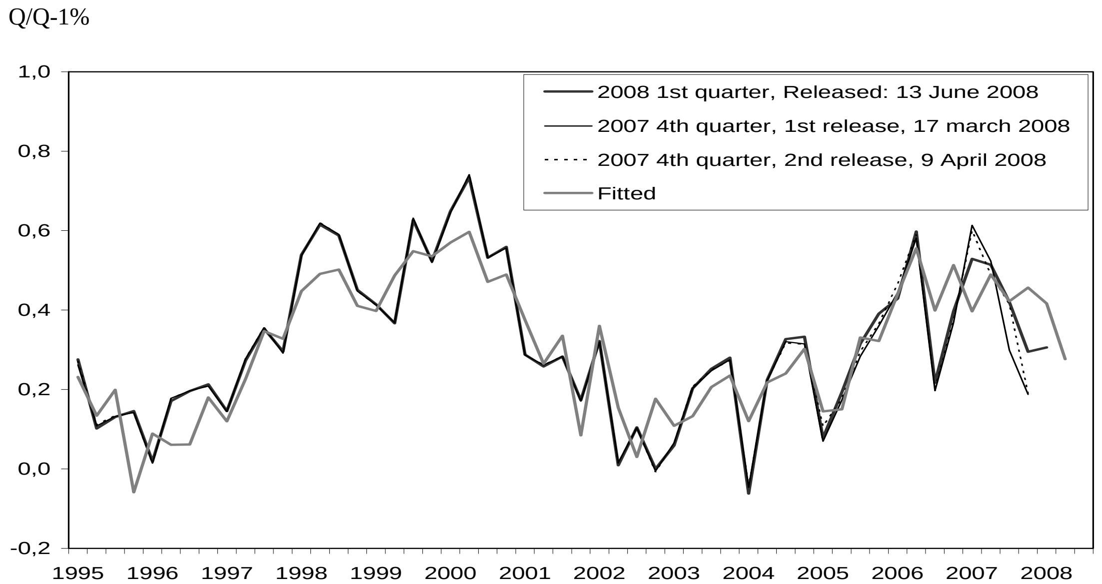
Figure 10 shows the actual and fitted employment growth rates using data available up to June 2008. The quarterly fluctuations are in general rather well depicted, although they are less pronounced than current official data suggest in the case of large shifts over a quarter.

Figure 10: Actual and fitted quarterly euro area employment growth rates 1992:2 – 2008:1



We have so far no real time data set available for employment. From our recent experience, it seems that latest employment quarterly growth rates can be significantly revised from a release to another. Figure 11 shows that between the March, April and June 2008 releases, employment quarterly growth rates were slightly revised back to 2004 and more substantially in 2007 and 2008. The latest figures are closer to our model estimates based on survey data. It remains to be checked whether this holds over a longer period of time.

Figure 11: Different releases and fitted quarterly euro area employment growth rates 1995:1 – 2008:1



7.2 Out-of-sample errors over the last three years (2004Q1-2008Q1)

We examine the errors that would have been made with our model since 2004Q1. Employment quarterly growth estimates are computed with data available in June 2008, not with real time data, and so only one estimate per quarter is produced. Estimate errors are thus derived from the actual employment series. Table 10 shows that the root mean squared error of these estimates equals R1=0.1 point. The out-of-sample estimate of employment quarterly growth is plotted on figure 7 and compared to the series available in June 2008.

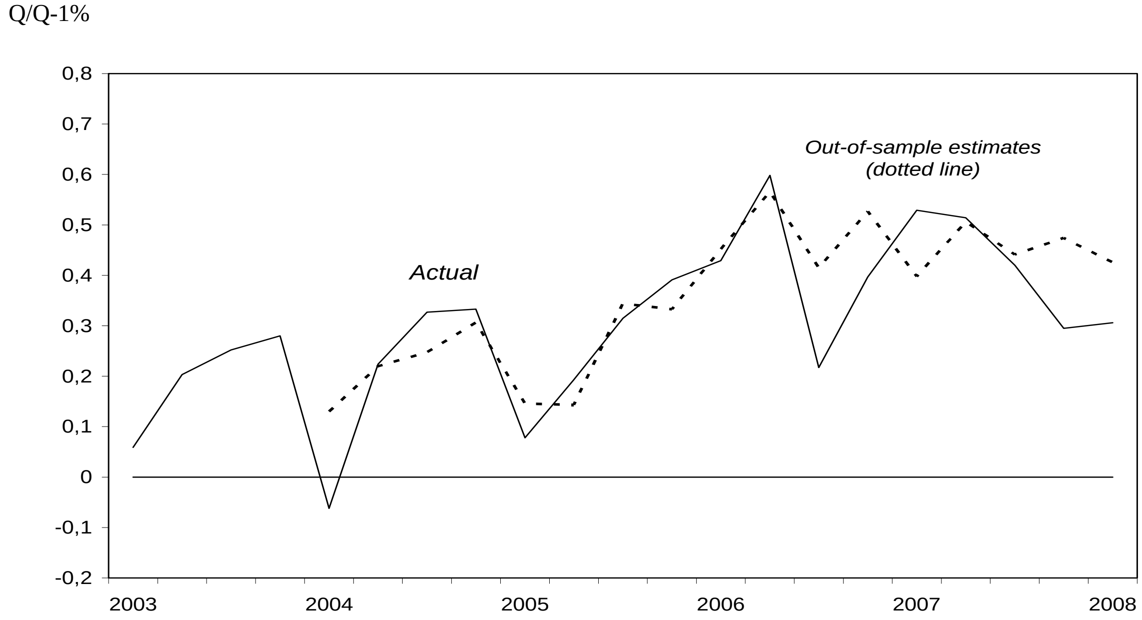
The first question we have to address is whether this estimate performs better than an autoregressive model. The best autoregressive model is found to be an AR(1). The out-of-sample forecasts over (2004Q1-2008Q1) are computed with, as previously, an equation re-estimated each quarter and the associated RMSE equals R4=0.17 point (see Table 10). The Diebold-Mariano test rejects the assumption that the two RMSE are equal (p-value=0.2%) against the assumption that our equation gives smaller RMSE than the autoregressive model.

Table 10: Root Mean Squared Errors and Diebold-Mariano tests

In percentage point

Type of errors	RMSE	P-value of Diebold-Mariano test $R_i = R_j$ versus $R_i < R_j$
Out-of-sample errors (equation re-estimated each quarter)	R1 = 0.102	R1=R4 vs R1<R4 0.2%
In-sample errors (equation estimated until 2008q1)	R2 = 0.100	R1=R2 vs R2<R1 2.1%
Out-of-sample errors (equation estimated until 2003Q3)	R3 = 0.101	R2=R3 vs R2<R3 5.3%
Out-of-sample errors with an AR(1) equation re-estimated each quarter.	R4 = 0.170	

Figure 12: Employment quarterly growth rates:
actual and out-of-sample estimates since 2004Q1



We compare the out-of-sample errors of our model (RMSE R1) with its in-sample errors (RMSE R2 equal to 0.1 point), in other words the adjustment errors obtained with the most recent fit (presented in the previous section). The Diebold-Mariano test rejects the assumption that the two RMSE are equal but the p-value is not close to zero (it is equal to 2.1%). The chart (not plotted here) shows that the two series of errors are very similar.

In order to check the stability of the equation, we estimate our equation until 2003Q4 and compute the out-of-sample errors obtained with this equation and the associated RMSE R3. The Diebold-Mariano test accepts the assumption that the two RMSE R2 and R3 are equal which allows us to conclude that the equation is stable.

Our model for euro area employment quarterly growth rate does not perform too badly. The equation has a major advantage in a regular production process: it includes only survey data which are very rapidly available and generally not revised.

8. 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 of the chosen approach: regressions with individual series or with principal components. Following the revision of industrial production including construction in late 2007, 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 data sets imply that it is necessary to re-consider regularly the list of individual series entering models that produce estimates of euro area indicators. 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.

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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 euro area share prices (in real terms), the growth rate of the real dollar-euro exchange rate, the real oil price growth rate. We extract factors using principal component analysis carried out on standardized data, i.e. 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 area)
REAL EXCHANGE RATE – U.S. $ TO EURO
REAL OILBREN PRICE
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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 equals 0.20 percentage point whatever the estimation date (see Table A2). The estimates are unbiased (Table A2). This model, called SW-model, is compared with our PC-model using the Diebold-Mariano test. The performance of the SW model is clearly lower for two estimation dates (see 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%