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Leading indicators for Euro-area inflation and GDP growth [*]

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Abstract

In this paper we evaluate the role of a set of variables as leading indicators for Euro-area inflation and GDP growth. Our evaluation is based on using the variables in the ECB Euro-area model database, plus a set of similar variables for the US. We compare the forecasting performance of each indicator with that of purely autoregressive models, using an evaluation procedure that is particularly relevant for policy making. The evaluation is conducted both ex-post and in a pseudo real time context, for several forecast horizons, and using both recursive and rolling estimation. We also analyze three different approaches to combining the information from several indicators. First, we discuss the use as indicators of the estimated factors from a dynamic factor model for all the indicators. Second, an automated model selection procedure is applied to models with a large set of indicators. Third, we consider pooling the single indicator forecasts. The results indicate that single indicator forecasts are on average better than those derived from more complicated methods, but for them to beat the autoregression a different indicator has to be used in each period. A simple real-time procedure for indicator-selection produces good results.

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1. Introduction

Inflation and GDP growth are probably the two most important macroeconomic variables, as they drive monetary and fiscal policy. Methods for forecasting these two variables have been the subject of much intensive research in econometrics. Recent papers focusing on the US experience include the use of univariate leading indicator models (Cecchetti, Chu and Steindel (2000)), of factor models (Stock and Watson (1998,1999)), and of automated procedures using systems of leading indicators (Camba-Mendez, Kapetanios, Smith and Weale (2001)). Banerjee and Marcellino (2003) compare all these approaches for the United States and find that single indicators are in general the best-performing from a forecasting point of view, but with the best indicator changing over time.

Several studies are by now available also for the Euro area. For example, Marcellino (2002a) evaluates the performance of a large set of univariate forecasting methods, finding that simple autoregressive models perform well although for some series using nonlinear methods produces forecasting gains. Marcellino, Stock and Watson (2003) adopt factor models for forecasting industrial production, inflation and unemployment both for the Euro area as a whole and for its member countries, and find some gains with respect to autoregressions, in particular for nominal variables. Fagan, Henry and Mestre (2001) construct a medium scale macroeconometric model for the Euro-area variables, forecasts from which, in general, outperform those derived from time-series models.

The aim of our analysis is to conduct a detailed evaluation of the properties of a large set of leading indicators for Euro area inflation and GDP growth, using not only Euro-area series but also US macroeconomic variables. Received wisdom suggests, for example, that the links between the US and the Euro area could be important, with Euro-area growth depending upon US growth, and the European Central Bank's (ECB) decisions following in part the policies of the Federal Reserve Board (Fed). Marcellino et al. (2003) find few gains from using US industrial production and inflation for forecasting their Euro-area counterparts. Here we conduct a more detailed analysis by evaluating a larger set of US indicators.

Following Banerjee and Marcellino (2003), we first compare the performance of single indicator models with pure autoregressions. Next, we exploit the joint information set in three ways. First, we model all the indicators by means of a dynamic factor model and use the estimated factors as leading indicators. Second we jointly consider groups of indicators and an automated model selection procedure to obtain a parsimonious forecasting model.

Third and finally, we adopt pooling procedures to combine the single indicator based forecasts.

The evaluation of these competing forecasting procedures is based on a particular criterion that is most relevant for policy making, where the same model is adopted for forecasting at several horizons, it is periodically evaluated (and possibly re-specified and/or re-estimated), and the goal is to obtain robust forecasts that perform well on a year by year basis and not only on average over a long period of time. This criterion is denoted by RMSE-*h* and described in detail below.

The comparison is conducted using both an ex-post and a pseudo ex-ante approach. In the ex-post evaluation, future values of the exogenous regressors are assumed known to evaluate the informational content of the indicators independently of their forecastability. This provides the maximum advantage against the autoregressive models but, as we will see, in many cases it is not enough to outperform them. In the ex-ante framework, no future information is used, future values of the regressors are forecast, and the choice of the indicators is based on their past forecasting records. This provides an indication for the construction of feasible leading indicator forecasts.

The paper is organized as follows. In Section 2 we briefly review the forecasting methods under analysis. In Section 3 we discuss the Euro-area and the US datasets. In Sections 4 and 5 we present the results of the forecasting exercise for, respectively, inflation and GDP growth. Some sensitivity analysis is conducted to judge the robustness of the exercise. In Section 6 we summarize the main results and conclude.

2. The methodology

In this section we describe the forecasting methodologies used by us and the evaluation criterion we adopt to rank the competing methods. We deal in turn with single indicator forecasts, factor forecasts, automated model selection based forecasts, forecast combination procedures and, finally, the forecast evaluation criterion.

2.1 Single indicator forecasts

The estimated model takes the form

$$Y_t = \alpha + \Sigma_{i=1}^{m} \beta_i Y_{t-i} + \Sigma_{i=1}^{k} \delta_i IND_{t-i} + \varepsilon_t , \qquad (1)$$

where Y_t is the variable of interest and IND_{t-i} is the i$^{\text{th}}$ lag of the particular indicator variable chosen. The values of m and k are determined by the automated model selection procedure described below, since Banerjee and Marcellino (2003) found in general gains from using this approach to determine the number of lags instead of a fixed lag length. Pure autoregressions are a special case of (1) when the indicator variables are excluded.

The model (1) is used to produce one- up to h-step ahead forecasts of the Y variable, and compared with the forecasts arising from an autoregressions (where the number of lags in the pure autoregression are also always chosen using an automatic model selection algorithm). Stock and Watson (1998, 1999) and Marcellino (2002a) use dynamic estimation instead. Since this latter method requires us to specify and estimate a different model for each forecast horizon, it is computationally cumbersome in our context with several horizons and many indicators.

Whenever out-of-sample values of the Y variable are required to generate forecasts, the forecast value is used. In the ex-post evaluation, unknown values of the leading indicator variable are replaced by the actual values. This framework biases the analysis in favour of the indicator model versus the pure autoregressive model and is adopted to evaluate the information content of the indicator, which could be hidden by its poor forecastability. We will also consider a pseudo ex-ante context where unknown values of the leading indicator variable are replaced by forecasts from autoregressive models.

2.2 Factor based forecasts

Dynamic factor-models can provide an efficient tool for extracting information from a large database, so that instead of a single indicator variable we can use the estimated factors from a set of indicators to forecast the variable of interest. This forecasting technique has recently been successfully applied to forecasting US, UK and Euro-area macroeconomic variables (Stock and Watson (1998), Artis, Banerjee and Marcellino (2001) and Marcellino et al.(2003) respectively), with some differences in the type of variables for which the forecasting gains are larger, typically real variables in the US and nominal variables for Europe. Here we briefly introduce the representation and estimation theory for the dynamic factor model, see for example Geweke (1977), Sargent and Sims (1977), Forni, Hallin, Lippi, and Reichlin (2000) and, in particular, Stock and Watson (1998) for details.

The N-macroeconomic variables to be modelled, grouped in the vector X_t, admit an approximate linear dynamic factor representation with $\bar{r}$ common factors, f_t, if:

$$X_{it} = \lambda_i(L) f_t + e_{it} \tag{2}$$

for i=*1,...,N*, where e_{it} is an idiosyncratic disturbance with limited cross-sectional and temporal dependence, and $\lambda_i(L)$ are lag polynomials in non-negative powers of *L*. If $\lambda_i(L)$ have finite orders of at most *q*, the model in (2) can be rewritten as,

$$X_t = \Lambda F_t + e_t \tag{3}$$

where $F_t = (f_t^{'}, \ldots, f_{t-q}^{'})'$ is $r \times 1$, where $r \leq (q+1)\bar{r}$, and the i-th row of Λ in (2) is $(\lambda_{i0}, \ldots, \lambda_{iq})$.

Stock and Watson (1998) prove that, under some technical assumptions (restrictions on moments and stationarity conditions), the column space spanned by the dynamic factors f_t can be estimated consistently by the principal components of the $T \times T$ covariance matrix of the *X*'s.[1] A condition that is worth mentioning for the latter result to hold is that the number of factors included in the estimated model has to be equal or larger than the true number. The empirical analyses mentioned above have shown that two or three factors are sufficient to explain a large proportion of the variability of a large set of time series. We estimate up to six factors in what follows, and use them for forecasting the variable of interest. Hence, the starting specification of the model for *Y* in this case is

$$Y_t = \alpha + \Sigma_{i=1}^{m} \beta_i Y_{t-i} + \Sigma_{j=1}^{6} \ \Sigma_{i=1}^{k} \delta_{j,i} f_{j,t-i} + \varepsilon_t \tag{4}$$

2.3 Automated model selection

PcGets is a computer-automated algorithm for general to specific reductions of models developed by Hendry and Krolzig (1999) and Krolzig and Hendry (2001), see also Hoover and Perez (1999). The starting point for the algorithm is the specification of a general unrestricted model (GUM) containing all variables likely (or specified) to be relevant, including the maximum lag length of the independent and dependent variables. The algorithm starts from a 'pre-search' simplification by applying tests for variable deletion, following which the GUM is simplified. This step uses a loose significance level such as 10%, to delete highly non-significant regressors. The procedure is refined at the second stage, where many alternative further reductions of the GUM are considered, using both *t* and *F* tests and information criteria as reduction (or deletion of variables) criteria. Diagnostic tests ensure that the models chosen as valid simplifications/reductions are congruent representations of the data. The third stage is the encompassing step (see *e.g.* Mizon and Richard (1986)) where all

[1] Notice that the fact that the column space rather than the factors themselves can be estimated is not problematic for forecasting since the column space provides an equivalent summary of the information contained in the data set.

valid reduced models from the second step are collected, and encompassing tests are used to evaluate the relative merits of these competing models. Only models that are not encompassed are retained. If more than one model survives the third stage, their union forms the new general model and the algorithm recommences. This process continues until the set of non-encompassed models reduces to one or the union is repeated.

We use *PcGets* first to select the lag length of the *Y* variable and of the indicator in model (1), starting with a maximum of 6 lags. Second, to determine what factors and how many lags should be used in the model (4), starting with 6 factors and 6 lags. Third, to simplify a general model where several indicators are jointly considered as explanatory variables for *Y*, i.e,

$$Y_t = \alpha + \Sigma_{i=1}^{m} \beta_i Y_{t-i} + \Sigma_{j=1}^{q} \ \Sigma_{i=1}^{k} \delta_{j,i} IND_{j,t-i} + \varepsilon_t \qquad (5)$$

We select the indicators to be included in the GUM (5) based either on economic criteria (real, nominal, financial variables) or on their forecasting performance as single indicators.

2.4 Forecast combination

The factor approach and the model simplification method are alternative, possibly complementary, procedures to summarize a large information set into a relatively small explanatory model for the *Y* variable, which is then used for forecasting. As an alternative, the information in the large set of indicators could be exploited by combining the single indicator forecasts.

Bates and Granger (1969) advocated the use of combination of forecasts as a tool to reduce the root-mean-squared forecast error (RMSE), and since then several studies have found this method useful, e.g. Stock and Watson (1999, 2001), see also Clements and Hendry (2002) and Marcellino (2002b). The weights should in principle depend on the entire covariance matrix of the forecasts to minimize the RMSE. Since this is too complicated in our framework with many forecasts, we will consider two simple procedures that have performed well in similar analyses, e.g. Stock and Watson (1999, 2002). First, a simple average of all the single indicator forecasts, and second the median of the forecasts. The latter could be more robust since we will see that some indicators produce forecasts with high RMSEs in some periods.

2.5 Forecast evaluation

The models in (1), (4) and (5) are estimated with a starting sample of 10 years, and are then re-estimated adding one year each time. For each estimation period, one- up to eight- quarters-ahead forecasts are computed, and the loss function is constructed as the square root of the average squared forecast errors one- up to eight-steps ahead, denoted by RMSE-*h*. For example, in the case of inflation, the models are estimated first from 1975:1 to 1984:4 to provide forecasts for the eight quarters up to 1986:4. The estimation sample is next augmented by one year (*i.e.* until 1985:4) and the models are re-estimated to forecast inflation for the 1986-87 period. This exercise of augmentation is continued recursively until the estimation sample extends to 1998:4 and forecasts are provided for the 1999-2000 period.

This procedure, adopted for example by Cecchetti et al. (2000), differs from the standard practice of taking averages over the whole forecasting period of the forecast errors computed for a fixed horizon. Its main advantage is that it is closer to the practice of forecast evaluation by policy makers and practitioners, where the same model is used to forecast at different horizons and the interest is in the periodic evaluation of the model (and possibly in its periodic re-specification). This is done since we wish to keep track of forecasting performance over the estimation and forecasting samples recursively, instead of simply comparing average forecasting accuracy. Another important benefit is that the evaluation is more robust to structural changes over the forecast samples, which are quite frequent, see e.g. Stock and Watson (2001).

We also argue that the use of the standard average of the fixed horizon root-mean-squared errors over a reasonably long period of time can be misleading, by hiding many interesting characteristics of the indicators. In particular, some indicators can outperform autoregressive models on average but forecast very poorly in some periods. This has serious consequences if the forecasts are used in a policy making environment. The fact that the indicators should be changed from period to period, depending on the likelihood of particular economic shocks over the forecasting period, does not emerge under the choice of a loss function which averages over time.

The main drawback of our approach is that since the series of the computed RMSE-*h* statistics is short and its elements are highly correlated, it is not possible to provide a reliable statistical test for a significant difference in forecasting performance. Nevertheless we think that the point RMSE-*h* estimates provide a clear ranking of the competing forecasting models.

3. The Data

The construction of quarterly Euro-area data for a long enough time span is complicated. A partial list of the problems includes the choice of the aggregation method (fixed versus time-varying weights, role of exchange rates, choice of the proper weighting variable, etc.); the presence of major redefinitions and institutional changes (modifications in the national accounting systems, the German reunification, etc.); the presence of missing observations and the need to disaggregate annual figures for some countries into quarterly values; and the choice of the seasonal and working day adjustment methods (for example whether to seasonal adjust the national series or directly the aggregated variable).

To focus on the topics of the paper, we have decided to use as a starting point an already existing and widely use dataset, the one constructed by Fagan, Henry and Mestre (2001) for the ECB Euro-area-wide model. The dataset includes quarterly data for the period 1970:1-2000:4, for several macroeconomic variables, mainly constructed using the so-called "Index Method". For example, the logarithm of the Euro-area GDP is a weighted sum of the logarithms of the country specific GDPs, with constant weights based on the 1995 real GDP share.[2] We have then added some other indicators to reflect the choice of variables in Stock and Watson (1999, 2001), even though many fewer series are available for the Euro area as a whole than for its member countries or the US.

We consider 46 Euro-area variables as indicators, listed in the Data Appendix (which also describes the type of data transformation adopted). They include output variables such as GDP, industrial production and some of their components; employment and productivity indicators; wages; exchange rates; interest rates and spreads; monetary aggregates; price indexes; and some other miscellaneous variables. Industrial production, some monetary aggregates and producer prices come from Eurostat and are available for a shorter time span.

To the list above we add 16 US variables that broadly reflect the groupings of European indicators, to evaluate their role in forecasting Euro-area series. For the US we also consider as indicators the factors extracted from the larger dataset in Banerjee and Marcellino (2003), that covers the sample 1975:1-2001:4 and includes about 50 indicators, listed in their Data Appendix.

[2] More sophisticated aggregation methods have been suggested, e.g., by Beyer, Doornik and Hendry (2001), but they have produced a very limited number of (monthly) Euro area series.

4. Forecasting Inflation

4.1 Euro-area and US indicators

We have 46 indicators, fewer in the early periods, whose performance in the 15 evaluation periods is summarized in Tables 1a and 2a. Four main comments are in order.

First, the autoregression yields a lower RMSE-*h* than at least 50% of the models with an indicator in 10 out of the 15 periods. Second, the best performing indicator is always better than a pure autoregression. However, the best indicator changes over time, likely to reflect he different shocks that hit the Euro area over the period under analysis, and no indicators are best more than twice. Third, 12 out of the 46 indicators do better than the autoregression more than half of the time. These can be grouped into four categories, namely: (i) labour market variables, including unemployment, employment and the growth of wages and of productivity; (ii) particular prices, mainly the commodity prices and the private consumption deflator; (iii) fiscal variables, mainly expenditure and receipts and (iv) two real variables, the growth rate of GDP and of gross investment. Finally, among the worst performing indicators there are, rather surprisingly, total demand, total industrial production, and the short term interest rate, while the long term one performs much better.

As far as the US indicators are concerned, their performance is summarized in Table 3. The best variable is the US inflation rate that outperforms the autoregression in 11 out of 15 cases, but never produces the best forecast. The other good indicators are also reasonable from an economic point of view, they are the capacity utilization rate, the growth of M2, a 3-month interest rate, the growth in hourly earnings and the growth in the real exchange rate.

Since the dynamic properties, particularly the persistence of the inflation series , (whether I(0) or I(1)), are open to doubt, our analysis is repeated in order to forecast the first difference of inflation (with the right-hand-side or leading indicator variables for nominal or price variables correspondingly differenced twice). The results are reported in Tables 1b and 2b where the dominance of the autoregressive method is even more evident when compared to Tables 1a and 2a

4.2 Factor-based forecasts and groups of indicators

In Table 4 we summarize the forecasting performance of US and Euro-area factors. As mentioned previously, the US factors are extracted from the dataset in Banerjee and Marcellino (2003) that includes a larger selection of variables, similar to the one we use here for the Euro area. The European factors are instead extracted from the full dataset in Fagan et al. (2001). In both cases we consider the first six factors that explain a fraction larger than 50% of the variance of all the indicators.

There are two Euro-area factors and one US factor that do better than the autoregression more than half the time, and it is interesting to point out that they are not those with the highest explanatory power for the indicators (a related fact is that the first US factor is systematically deleted). Other factors, for example number one for the Euro area and number six for the US also perform well. But no factor produces the best forecast more than once and the best single indicator usually beats each of them.

To evaluate whether grouping helps, we next consider the forecasting ability of models for ten different groups of indicators, with the exact specification of the forecasting model being sequentially determined by *PcGets* using either a conservative or a liberal strategy (the former minimizes non-deletion probability and includes a variable if the deletion statistic rejects at 1%, the latter minimizes non-selection probability and uses a 5% significance value).

The variables to be included in the groups are selected either on the basis of their forecasting performance as single indicators, or on their belonging to a certain category (e.g., real or financial variables, or factors), or a combination of the two methods. A precise list of the variables in each group is reported in Table 5 that also summarizes the results.

Three main comments can be made. First, the ranking of the two variable-selection strategies (conservative and liberal) is unclear. Second, for both selection methods the best groups are group 4 (best 5 single indicators), group 6 (the 6 US factors) and group 7 (the 6 Euro-area factors). The good performance of the factors once grouped confirms a finding in Marcellino et al. (2003) that only considered Euro-area factors, and is different from the outcome for the US where the factors perform better for real variables (see Stock and Watson (1998) and Banerjee and Marcellino (2003)). Group 2, consisting of financial indicators and prices, also outperforms the autoregression in most cases, but is itself often dominated by another group forecast. Finally, the single indicator forecasts are also often beaten by the groups, 6 out of 9 times with a conservative selection strategy and 4 out of 9 times with a liberal strategy, but the fact that the best group varies substantially over time makes a real-time implementation of the grouping approach problematic.

4.3 Sensitivity Analysis

To evaluate the robustness of the previous results, in this subsection we change both method of estimation, using a rolling window of 10 years rather than a recursively extended sample (see e.g. Pesaran and Timmermann (1995)), and forecast horizon, focusing on up to one year ahead forecasts, i.e. h=4 rather than h=8.

Table 6 reports the results for rolling estimation, to be compared with those in Table 1a. It turns out that the RMSE-h is lower with rolling than with recursive estimation in only 5 out of 15 cases for the autoregressive model and 4 out of 15 cases for the best single indicator model, and in most of these cases the gains are minor.[3] On the basis of these figures, recursive estimation appears to be preferable.

The performance of single indicators for h=4 with recursive method is summarized in Tables 7 and 8. With respect to the h=8 analysis (in Tables 1a and 2a) the best indicator changes over time and the gains it generates with respect to the autoregressive model are on average larger, while the list of good indicators is basically unaltered. Similar results are obtained for the shortest horizon, i.e. h=1, the tables for which are available upon request.

4.4 Forecast pooling

Table 9 reports the ratios of the RMSEs-h of the pooled forecasts relative to the autoregression benchmark, using recursive estimation for h=4 and h=8. Two main comments can be made. First, the median always outperforms the average forecasts, due to some high RMSE-h indicator-based forecasts. Second, when h=4 the median forecasts are at least as good as the autoregression in 6 out of 16 evaluation periods, in 5 out of 15 when h=8. Not surprisingly, these periods are those when a large fraction of single indicators beat the autoregression forecast, compare Tables 1a and 7

4.5 Pseudo real time analysis

We have assumed so far that future values of the indicators are known when forecasting. This is the scenario which provides the most favourable environment for the use of indicators, in the sense that if they do not perform well here they can be expected not to do so in real time. In fact, we have found that single indicators or groups can outperform the autoregression but the choice of the indicator or group has to be continuously updated. In this section we evaluate whether the autoregression can be also beaten in a pseudo-real-time framework, focusing for simplicity on single indicator forecasts.

[3] A similar finding emerges for h=4.

Our method of ex-ante evaluation can best be described by an example. Say that we are in the last quarter of 1992 and want to produce forecasts for 1993:1 until 1994:4. Then we can use 1990:4 for estimation and produce forecasts for 1991:1 until 1992:4 and compute the RMSE-*h* for each indicator (at this stage we still use future values of the indicators to produce the forecasts since they are in the available information set). The indicator that provides the lowest RMSE-*h* for 1991:1 until 1992:4 is then used to forecast from 1993:1 until 1994:4, where the estimation sample is extended until the last available observation, i.e., 1992:4. Moreover, since values of the indicator variable over the period 1993:1 until 1994:4 are not known in 1992:4, autoregressive models are used to forecast them.

The procedure above is repeated for each year, starting in 1990:4 in order to have enough observations in the first evaluation period, and the results are reported in Table 10 for h=1, h=4 and h=8. The findings are encouraging for h=4, i.e. when forecasting up to one year ahead, when the indicator beats the autoregression in 7 out of 10 periods, and the gains are usually substantial. The performance deteriorates for both the shorter (h=1) and longer horizon (h=8), when the autoregression can be beaten in only 3 out of 10 and 2 out of 9 cases respectively.

5. Forecasting GDP growth

5.1 Euro-area and US indicators

We now evaluate the ability of the 46 indicators under analysis for forecasting GDP growth, starting with the comparison of each indicator with the autoregressive benchmark. Tables 11 and 12 present the results, and three main comments can be made.

First, the autoregression yields a lower RMSE-*h* than at least 50% of the models with an indicator in 12 out of the 15 periods, even more often than for inflation. Second, the best performing indicator remains always better than a pure autoregression but changes over time, with no indicator being the best more than twice. With respect to inflation, more indicators are deleted by *PcGets* because of statistical insignificance in the forecasting regressions. Third, only 5 out of the 46 indicators do better than the autoregression more than half of the time, versus 12 indicators in the case of inflation. They are the short-term interest rate, public expenditure, total industrial production, and world GDP and demand growth. Employment and unemployment variables can be also included in the set of good indicators.

As far as the US indicators are concerned, from Table 13 the best indicators are the short and long-term interest rates, the growth in the NYSE share prices, labour market variables such as hours worked and unemployment, and the consumer confidence indicator. Perhaps surprisingly, US GDP and industrial production growth outperform the autoregression only in 4 out of 15 evaluation periods.

5.2 Factor based forecasts and groups of indicators

The forecasting performance of US and Euro-area factors is summarized in Table 14. The first US factor, which was systematically deleted in the case of inflation, is instead the best performer for GDP growth. None of the Euro-area factors works well, which is in line with the finding in Marcellino et al. (2003) that factors work better for nominal than for real variables, in contrast with the US (see also Stock and Watson (1998), Banerjee and Marcellino (2003)).

Table 15 reports results for groups of indicators and factors, where the groupings are given as for inflation and the model specification is sequentially determined by *PcGets* using either the conservative or the liberal strategy, with the former slightly outperforming the latter. It turns out that the best groups include the best Euro-area or US single indicators, with the latter doing better than the autoregression in 6 out of 9 cases. However, the best single indicator systematically beats the best group, a finding that provides further support in favour of simple models.

5.2 Sensitivity Analysis

The relative ranking of rolling and recursive estimation is less clear cut than in the case of inflation. As may be seen from Table 16 the former yields a lower RMSE-*h* than the latter in 7 out of 14 evaluation periods, both for the autoregression and for the best single indicator model, but in most of these cases the gains are minor. We therefore continue the analysis using recursive estimation only, but results for rolling are available upon request.

Tables 17 and 18 summarize the performance of the single indicators for h=4. As for inflation, with respect to the h=8 analysis (in Tables 11 and 12), the best indicator changes and the gains it generates with respect to the autoregressive model are on average larger. The fraction of times when at least 50% of the indicators beat the autoregression slightly increases to 5/16, while the list of the overall best performing indicators is not affected by the change in forecast horizon.

For the shortest horizon, *i.e.* h=1, for which the results are available upon request, there is evidence in favour of the efficacy of using leading indicators. For example, the fraction of times when at least 50% of the indicators beats the autoregression shows a substantial increase to nearly 8 out of 16 cases and similar gains are recorded in the performances of individual indicators.

5.3 Forecast pooling

The ratios of the RMSEs-h of the pooled forecasts relative to the autoregression benchmark are reported in Table 19. Two main comments can be made. First, as for inflation, the median always outperforms the average forecasts. Second, the median forecasts are at least as good as the autoregression in only 3 out of 16 evaluation periods for h=4 and 8. In comparison with the results reported in section 4.4 for inflation, the weaker performance of the pooled forecasts for GDP growth may be justified by the poorer than average performance of the single indicators for forecasting GDP growth.

5.4 Pseudo real time analysis

The outcome of the pseudo real-time analysis is less encouraging than for inflation, except for the shortest horizon, as can be seen from Table 20. For h=1, the indicator beats the autoregression in 7 out 10 periods. At the longer horizons, i.e. h=4 and 8, the indicator beats the autoregression in 4 out of 10 and 3 out of 9 periods respectively, with rather minor gains.

6. Conclusions

This paper has presented a thorough analysis of leading indicators for Euro-area inflation and GDP growth. We consider many single (European and US) indicators, factors extracted from the set of indicators, groups of indicators or factors (with the final specification determined by an automated model selection procedure), and pooled forecasts. The comparison is with respect to an autoregressive model, the loss function is particularly relevant in a policy making context, and we conduct the analysis both ex-post and in a pseudo-real time context, for up to one year and up to two year forecasts.

Seven main conclusions can be drawn for forecasting Euro-area inflation. First, ex-post, autoregressions are systematically beaten by univariate leading indicator models, but the best indicator changes over time. This is reflective of the fact that the dynamics of the variable forecast will be driven by different shocks at different points of time, so that different indicators will assume different relevance over different time periods. Thus, even in the best case scenario – i.e. under ex-post evaluation – autoregressions (sufficiently differenced for stationarity), which are simple models, will be overall the most robust forecasting tool. One could consider extending this class of cases to include ARMA models but this would take us beyond the scope of the current analysis. Second, some labour market variables, prices, fiscal series and the GDP growth rate on average outperform the autoregression. Third, some US indicators are also useful, in particular the inflation rate, the capacity utilization rate, the growth of M2, a 3-month interest rate, the growth in hourly earnings and the growth in the real exchange rate. Fourth, grouping either the best performing single indicators or the US or Euro-area factors, complemented by the automatic model selection procedure implemented with *PcGets*, is often better than the autoregression, but no group systematically beats it. Fifth, recursive estimation appears to be better than rolling estimation, and the indicators appear to perform better for a one year horizon than for a two year one. Sixth, the median pooled estimator performs better than the mean, better than the autoregression in a few cases.. Finally, in a pseudo ex ante context, the indicators can beat the autoregressions quite often when h=4, but not when h=1 or h=8.

Seven similar comments can be made for Euro-area GDP growth, besides the general statement that the indicators used in this paper on average appear to perform better for inflation. First, ex-post, univariate leading indicator models can always beat the autoregression, but the best indicator changes over time. For the shortest forecasting horizon, the use of leading indicators for GDP growth appears to have some value. Second, the best indicators on average are the short-term interest rate, public expenditure, total industrial production, and world GDP and demand growth. Third, the set of good US indicators includes the short and long-term interest rates, the growth in the NYSE share prices, labour market variables such as hours worked and unemployment, and the consumer confidence indicator, while rather surprisingly US GDP and industrial production growth are outperformed by the autoregression in most cases. Fourth, the best groups include the best Euro-area or US single indicators, but the best single indicator systematically beats the best group. Groups of factors do not perform particularly well, as well as the single factors, with the important exception of the first US factor. Fifth, there is no clear ranking of recursive and rolling estimation, while as for inflation the indicators appear to perform better for a one year horizon than for a two year one. Sixth, the median pooled estimator beats the mean, but is beaten more often by the autoregression than for inflation. Finally, in a pseudo ex ante context, the indicators can beat the autoregressions just in few evaluation periods.

Further work currently being undertaken by us includes evaluating the use of leading indicators under alternative loss functions. With a more standard loss function we could, for example, undertake density forecast comparisons or use Diebold-Mariano- type statistics. We are also pursuing the potential benefits from looking at the possible use of more detailed survey data (on consumer or business confidence, for example) or more disaggregate data (such as the components of a price index) in constructing forecasts. Most importantly, we are also considering the use of these methods to data from accession countries, where questions of inflation and GDP growth are of paramount importance in the years ahead and pose a considerable challenge to economists and forecasters alike.

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List of variables and transformations used

Variable	Trans	Description
Output variables		
YER	DLV	GDP
IPtot	DLV	Industrial production – total, series starts in 1978q1
IPman	DLV	Industrial production – manufacturing, series starts in 1980q1
YGA	LV	Output gap
FDD	DLV	Total demand
PCR	DLV	GDP – private consumption at constant prices
PCN	DLV	GDP – private consumption at current prices
PYR	DLV	Household's disposable income
GCR	DLV	GDP – government consumption at constant prices
GCN	DLV	GDP – government consumption at current prices
GEN	DLV	Government expenditure
ITR	DLV	gross investment in real terms
ITN	DLV	gross investment in nominal terms
YWR	DLV	World GDP
YWRX	DLV	World Demand Composite Indicator
Employment and productivity		
LNN	DLV	Total Employment
LN/LF	LV	Ratio Total Employment/Labour Force
LPROD	LV, DLV	Labour Productivity
URX	LV	Unemployment Rate
TFT	DLV	Trend Total Factor Productivity
Exchange rates		
EER	LV, DLV	real effective exchange rate
EEN	LV, DLV	nominal effective exchange rate
Interest rates and spreads		
LTN	LV	Long-term interest rate (% p.a.)
STN	LV	Short-term interest rate (% p.a.)
Spread	LV	LTN-STN
Monetary aggregates		
M1N	DLV	monetary aggregate M1, series starts in 1980q1
M3N	DLV	monetary aggregate M3, series starts in 1980q1
Price indexes		
HICP	DLV	HICP (1996=100)
PCD	DLV	Private consumption deflator
PPItot	DLV	Producer prices – total industry, series starts in 1980q1
PPIman	DLV	Producer prices – manufacturing, series starts in 1985q1
COMPR	DLV	Commodity Prices (HWWA)

Wages

WIN	DLV	Compensation to employees
WRN	DLV	Wage rate
ULC	DLV	unit labor costs

Miscellaneous

GDN_YEN	LV	Ratio Public Debt/GDP
GEN_YEN	LV	Ratio Government Expenditure/GDP
GPN_YEN	LV	Ratio Government Primary Surplus/GDP
GRN_YEN	LV	Ratio Govrnment Revnue/GDP
CAN	LV	current account balance
TBR	LV	Trade balance
MTR	DLV	Imports of Goods and Services
XTR	DLV	Exports of Goods and Services
confind	LV	Industrial confidence indicator, series starts in 1985q1
ecsent	LV	Economic sentiment indicator, series starts in 1985q1

US variables

GDP	DLV	GDP – Total (BN $, 1996 prices, S.A.)
ip	DLV	Industrial production – total (1995=100, S.A.)
cap	LV	Capacity utilization rate (%, S.A.)
lhman	LV	weekly hours worked – manufacturing (hours, S.A.)
lurat	LV	unemployment rate (% of civilian labor force, S.A.)
fs	DLV	NYSE share prices (1995=100)
fy10gov	LV	government composite bonds (>10 years, % p.a.)
fcod	LV	certificates of deposits (3 month, % p.a.)
Spread3m	LV	fcod – Federal Funds rate
Spread10y	LV	fy10gov – Federal Funds rate
ereff	DLV	US real effective exchange rate (1995=100)
m2	DLV	monetary aggregate M2 (BN$, S.A.)
infl	LV	growth rate of CPI index (1995=100, S.A.)
whetot	DLV	hourly earnings – total private (1995=100, S.A.)
wc	DLV	unit labor cost – manufacturing (1995=100, S.A.)
conf	LV	consumer sentiment (1995=100, S.A.)

Transformations used: LV – levels, DLV – annual growth rate
All data for Euro Area have been seasonally adjusted at source (Eurostat) or using the SABL method (Fagan et al., 2001). The base year for all series is 1990 if not indicate otherwise.
US data have been collected from OECD Main Economic Indicators database. S.A. indicates that the data have been seasonally adjusted at source.

INFLATION INDICATORS FOR EURO AREA

Table 1a: Performance of indicators in forecasting inflation up to eight quarters ahead

	Number of Indicators That Performed		RMSE-*h*			*PcGets Deletes*
Estimation period	Better Than AR	Worse Than AR	AR	Best Indicator	Worst Indicator	
75:1 84:4	31	7	5.78	1.54 (COMPRg)	6.50 (LPROD)	URX, XTRg, YWRg
75:1 85:4	7	31	1.13	0.85 (PCDg)	(6.49) EER	
75:1 86:4	24	14	1.58	0.74 (EENg)	12.11 (Spread)	
75:1 87:4	22	18	1.59	0.76 (WRNg)	6.48 (GPN_YEN)	
75:1 88:4	19	21	1.39	0.89 (MTRg)	6.05 (GPN_YEN)	
75:1 89:4	20	23	1.42	0.79 (LN/LF)	3.91 (GCRg)	
75:1 90:4	7	36	1.08	0.79 (PCNg)	3.62 (M1Ng)	
75:1 91:4	13	30	1.71	1.37 (WINg)	3.86 (EEN)	GRN_YEN
75:1 92:4	12	31	1.63	1.15 (GCNg)	10.01 (MTRg)	EEN
75:1 93:4	8	35	1.05	0.88 (PCDg)	4.06 (GDN_YEN)	XTRg
75:1 94:4	8	38	1.12	0.97 (M1g)	2.71 (GDN_YEN)	EER, XTRg
75:1 95:4	23	23	1.08	0.85 (ULCg)	2.42 (TBR)	
75:1 96:4	12	34	1.09	0.77 (CAN)	4.55 (LN/LF)	GCNg, ULCg
75:1 97:4	25	21	0.98	0.81 (EERg)	51.56 (M1Ng)	
75:1 98:4	38	8	2.23	0.76 (GEN_YEN)	2.65 (M1Ng)	

“g” indicates growth rate of original variable

Table 1b: Performance of indicators in forecasting the difference of inflation up to eight quarters ahead

	Number of Indicators That Performed			**RMSE-*h***		***PcGets Deletes***
Estimation period	**Better Than AR**	**Worse Than AR**	**AR**	**Best Indicator**	**Worst Indicator**	
75:1 84:4	7	32	1.69	0.98 (Spread)	3.96 (ΔPCDg)	
75:1 85:4	28	14	1.31	0.85 (ΔEENg)	3.53 (YGA)	
75:1 86:4	16	28	1.07	0.59 (ΔCOMPRg)	2.54 (XTRg)	
75:1 87:4	13	33	1.10	0.85 (Spread)	2.40 (GEN_YEN)	
75:1 88:4	20	26	1.50	1.13 (EERg)	2.72 (ΔPCDg)	
75:1 89:4	14	38	1.11	0.64 (ΔPPItotg)	1.85 (M3Ng)	LN/LF, URX
75:1 90:4	15	37	0.90	0.73 (GDPg)	1.85 (ΔWINg)	GRN_YEN
75:1 91:4	15	37	1.91	1.70 (ΔWRNg)	2.66 (ΔPCDg)	GRN_YEN, LN/LF, URX
75:1 92:4	14	38	2.00	1.57 (COMPRg)	2.41 (ΔPCDg)	GRN_YEN
75:1 93:4	13	39	1.16	0.85 (WINg)	2.16 (PYRg)	CAN
75:1 94:4	20	36	1.28	0.61 (ΔM1Ng)	1.88 (confind)	CAN
75:1 95:4	20	36	1.10	0.59 (ΔM1Ng)	1.61 (GDN_YEN)	GRN_YEN
75:1 96:4	22	34	1.00	0.79 (PYRg)	1.50 (ΔPCDg)	GRN_YEN, XTRg
75:1 97:4	19	37	1.19	0.95 (IIPmang)	58.57 (TFTg)	XTRg
75:1 98:4	19	37	1.00	0.70 (LN/LF)	70.13 (TFTg)	

"g" indicates growth rate of original variable

Table 2a: Ranking the Inflation Indicators (8-quarter forecasts)

	Number of Times the Indicator				
	Outperforms Autoregression	Underperforms Autoregression	Produces Best Forecast	Produces Worst Forecast	Is Deleted
COMPRg	8	7	1	-	-
EEN	4	11	-	1	1
EENg	7	8	1	-	-
EER	4	11	-	1	1
EERg	7	8	1	-	-
FDDg	2	13	-	-	-
GCNg	7	8	1	-	1
GCRg	6	9	-	1	-
GDN_YEN	2	13	-	1	-
GENg	8	7	-	-	-
GEN_YEN	5	10	1	2	-
LN/LF	9	6	1	1	-
LPROD	4	11	-	1	-
LPRODg	8	7	-	-	-
LTN	7	8	-	-	-
Spread	4	11	-	1	-
PCDg	11	4	2	-	-
PCNg	9	6	1	-	-
PCRg	8	7	-	-	-
STN	3	12	-	-	-
ULCg	6	9	1	-	1
URX	10	5	-	-	1
WRNg	11	4	1	-	-
YGA	5	10	-	-	-
M3Ng	6	9	-	-	-
CAN	6	9	1	-	-
GPN_YEN	7	8	-	2	-
GRN_YEN	8	7	-	-	1
ITNg	9	6	-	-	-
ITRg	7	8	-	-	-
PYRg	7	8	-	-	-
IIPtotg	2	10	-	-	-
IIPmang	2	10	-	-	-
ecsent	2	3	-	-	-
confind	2	3	-	-	-
PPImang	3	2	-	-	-
PPItotg	2	8	-	-	-
WINg	7	8	1	-	-
TBR	2	13	-	1	-
MTRg	5	10	1	1	-
XTRg	7	8	-	-	3
YWRg	6	9	-	-	1
YWRXg	5	10	-	-	-
GDPg	9	6	-	-	-
TFTg	5	10	-	-	-
M1Ng	1	9	1	3	-

“g” indicates growth rate of original variable

Table 2b: Ranking the Difference of Inflation Indicators (8-quarter forecasts)

	Number of Times the Indicator				
	Outperforms Autoregression	Underperforms Autoregression	Produces Best Forecast	Produces Worst Forecast	Is Deleted
COMPRg	8	7	1	-	-
EEN	6	9	-	-	-
EENg	4	11	-	-	-
EER	6	9	-	-	-
EERg	4	11	1	-	-
FDDg	4	11	-	-	-
GCNg	2	13	-	-	-
GCRg	1	14	-	-	-
GDN_YEN	6	9	-	1	-
GENg	6	9	-	-	-
GEN_YEN	7	8	-	1	-
LN/LF	4	11	1	-	2
LPROD	6	9	-	-	-
LPRODg	3	12	-	-	-
LTN	7	8	-	-	-
Spread	9	6	2	-	-
PCDg	0	15	-	-	-
PCNg	8	7	-	-	-
PCRg	2	13	-	-	-
STN	7	8	-	-	-
ULCg	3	12	-	-	-
URX	5	10	-	-	2
WRNg	4	11	-	-	-
YGA	6	9	-	2	-
M3Ng	2	13	-	1	-
CAN	3	12	-	-	2
GPN_YEN	8	7	-	-	-
GRN_YEN	1	14	-	-	5
ITNg	4	11	-	-	-
ITRg	4	11	-	-	-
PYRg	5	10	1	1	-
IIPtotg	0	12	-	-	-
IIPmang	2	10	1	-	-
ecsent	3	2	-	-	-
confind	2	3	-	1	-
PPImang	2	3	-	-	-
PPItotg	4	6	-	-	-
WINg	7	8	1	-	-
TBR	6	9	-	-	-
MTRg	8	7	-	-	-
XTRg	6	9	-	-	2
YWRg	4	11	-	-	-
YWRXg	5	10	-	-	-
GDPg	5	10	1	-	-
TFTg	6	9	-	2	-
M1Ng	2	8	-	-	-
ΔCOMPRg	7	8	1	-	-
ΔEENg	5	10	1	-	-
ΔPCDg	2	13	-	5	-
ΔULCg	2	13	-	-	-

ΔWRNg	7	8	1	-	-
ΔM3Ng	7	8	-	-	-
ΔPPImang	2	3	-	-	-
ΔPPItotg	4	6	1	-	-
ΔWINg	2	13	-	1	-
ΔM1Ng	2	8	2	-	-

"g" indicates growth rate of original variable

Table 3: Forecasting performance of selected US variables for EURO inflation

	Number of Times the Indicator				
	Outperforms Autoregression	Underperforms Autoregression	Produces Best Forecast	Produces Worst Forecast	Is Deleted
GDPg	2	13	-	-	5
ipg	5	10	-	-	2
cap	8	7	-	2 (samples 92, 93)	1
lhman	5	10	-	1 (sample 97)	8
lurat	6	9	-	-	-
fsg	6	9		-	2
fy10gov	6	9	-	-	5
fcod	8	7		-	1
Spread10y	2	13	-	-	-
Spread3m	4	11	-	-	2
ereff	1	14	1 (sample 84)	2 (samples 87, 97)	-
ereffg	8	7	1 (sample 88)	-	-
m2g	8	7	-	-	4
infl	11	4	-	-	-
whetotg	9	6	2 (samples 86, 91)	1 (sample 95)	-
wcg	6	9	-	-	-
conf	7	8	-	-	-

"g" indicates growth rate of original variable

Table 4: Forecasting performance of US and EURO factors for Euro inflation

	Number of Times the Indicator				
	Outperforms Autoregression	Underperforms Autoregression	Produces Best Forecast	Produces Worst Forecast	Is Deleted
US-F1	0	15	-	-	15
US-F2	4	11	-	-	-
US-F3	7	8	-	-	-
US-F4	9	6	1 (sample 96)	1 (sample 90)	2
US-F5	3	12	-	-	6
US-F6	6	9	1 (sample 85)	-	1
EU-F1	6	9	1 (sample 90)	-	-
EU-F2	8	7	-	-	-
EU-F3	6	9	-	-	1
EU-F4	5	10	-	-	3
EU-F5	3	12	-	-	6
EU-F6	9	6	-	-	-

Table 5a: Performance of groups of variables in forecasting inflation up to eight quarters ahead (conservative strategy)

Estimation period	AR	RMSE-*h* Groups 1	2	3	4	5	6	7	8	9	10	Best single
75:1 90:4	1.08	5.54	1.43	2.33	**0.63**	**1.08**	**0.81**	2.17	1.11	**0.66**	2.28	0.79
75:1 91:4	1.71	**1.61**	**1.68**	**1.61**	1.77	1.76	**1.58**	1.82	2.35	**1.26**	1.79	1.37
75:1 92:4	1.63	1.86	**1.38**	2.62	2.15	1.64	**1.34**	2.54	1.72	8.18	1.72	1.15
75:1 93:4	1.05	**1.04**	**0.95**	**1.04**	1.36	**0.88**	**0.72**	1.23	1.15	12.43	11.26	0.88
75:1 94:4	1.12	1.13	1.18	1.13	**0.92**	**1.07**	**1.10**	1.25	1.44	13.43	2.28	0.97
75:1 95:4	1.08	**0.97**	**1.01**	**0.96**	**0.95**	**1.05**	1.20	**0.82**	1.35	3.41	2.16	0.85
75:1 96:4	1.09	1.16	**0.79**	**0.91**	**0.82**	**0.93**	**0.78**	**0.95**	**0.76**	3.92	2.71	0.77
75:1 97:4	0.98	1.43	1.21	1.53	1.35	1.25	**0.90**	**1.01**	1.09	3.29	2.32	0.81
75:1 98:4	2.23	**1.07**	**1.80**	**1.21**	**1.16**	**1.21**	**2.01**	**0.93**	**1.06**	**1.87**	**1.10**	0.76

BOLD indicates that the corresponding RMSE-*h* is smaller than the RMSE-*h* of the pure AR model.

Table 5b: Performance of groups of variables in forecasting inflation up to eight quarters ahead (liberal strategy)

Estimation period	AR	RMSE-*h* Groups 1	2	3	4	5	6	7	8	9	10	Best single
75:1 90:4	1.08	4.56	2.14	2.93	**0.63**	**0.83**	1.18	2.76	1.14	1.75	2.47	0.79
75:1 91:4	1.71	2.31	**1.63**	2.61	1.77	1.76	1.73	2.04	2.23	**1.38**	2.56	1.37
75:1 92:4	1.63	2.51	**1.27**	2.62	2.21	1.64	**1.55**	2.41	2.41	12.57	14.75	1.15
75:1 93:4	1.05	**1.02**	**0.92**	1.48	**1.02**	**0.88**	**0.88**	1.55	1.80	23.51	20.55	0.88
75:1 94:4	1.12	1.22	1.36	1.49	**1.07**	**1.07**	1.63	**1.01**	1.55	2.40	12.10	0.97
75:1 95:4	1.08	1.33	**0.96**	**0.96**	**1.05**	**1.05**	1.68	**0.95**	1.23	3.11	2.23	0.85
75:1 96:4	1.09	**0.71**	**0.78**	1.42	**0.93**	**0.93**	**0.68**	**0.96**	**0.86**	3.46	3.01	0.77
75:1 97:4	0.98	**0.86**	1.32	1.74	1.25	1.25	**0.98**	1.10	1.23	2.32	1.18	0.81
75:1 98:4	2.23	**1.32**	**1.42**	**1.07**	**1.18**	**1.37**	**2.06**	**0.93**	**1.24**	**1.87**	**1.29**	0.76

BOLD indicates that the corresponding RMSE-*h* is smaller than the RMSE-*h* of the pure AR model.

Table 5c: Groupings of Variables in Tables 5a

Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8	Group 9	Group 10
COMPR-g	COMPR-g	GEN-g	WRN-g	WRN-g	US factors	EURO factors	WRN-g	cap	WRN-g
GEN-g	EEN-g	GEN_YEN	URX	URX			URX	fcod	URX
LN/LF	EER-g	LN/LF	PCD-g	PCD-g			PCD-g	ereffg	PCD-g
LPRODg	Spread	LPRODg	LN/LF				US F3	M2g	cap
PCD-g	PCD-g	PCN-g	PCN-g				US F4	infl	fcod
PCN-g	WRN-g	PCR-g					EU F2	whetotg	ereffg
PCR-g	ULCg	URX					EU F6		M2g
URX									infl
WRN-g									whetotg
GRN_YEN									
ITNg									
GDPg									

“g” indicates growth rate of original variable

Group 1 – indicators outperforming the autoregression at least 50% of times (12 variables)
Group 2 – Financial indicators and prices
Group 3 – Best real variables from Table 2
Group 4 – best 5 variables from Table 2
Group 5 – best 3 variables from Table 2
Group 6 – 6 US factors
Group 7 – 6 EURO factors
Group 8 – best 3 variables from Table 2 + best factors
Group 9 – best 6 US variables from Table 4
Group 10 – best 3 variables from Table 2 + best 6 US variables from Table 4

Table 6: Performance of indicators in forecasting inflation up to eight quarters ahead, 10-year rolling window

Estimation period	Number of Indicators That Performed Better Than AR	Worse Than AR	AR	RMSE-*h* Best Indicator	Worst Indicator	*PcGets Deletes*
75:1 84:4	31	7	5.78	1.54 (COMPRg)	6.50 (LPROD)	URX
76:1 85:4	3	35	1.02	0.64 (COMPRg)	7.83 (TFTg)	LPRODg
77:1 86:4	18	20	1.78	0.86 (PCDg)	4.43 (Spread)	EER, EENg, EERg, FDDg, LPRODg, PCRg, GPN_YEN, ITRg, TBR, XTRg, YWRg, YWRXg, GDPg
78:1 87:4	23	17	2.20	0.85 (Spread)	4.41 (LPROD)	LN/LF, LPRODg, URX, YGA, CAN, GPN_YEN, TBR, MTRg, XTRg, YWRXg
79:1 88:4	20	20	1.60	0.96 (PYRg)	5.87 (LPROD)	LPRODg, GPN_YEN, MTRg, XTRg
80:1 89:4	27	16	2.36	0.80 (LN/LF)	3.56 (IIPmang)	
81:1 90:4	17	26	1.12	0.85 (M1Ng)	4.76 (EER)	
82:1 91:4	14	29	1.71	1.47 (GDPg)	3.37 (PPItotG)	GCRg, GEN_YEN, LPRODg, Spread, STN
83:1 92:4	6	37	1.43	1.16 (LTN)	3.93 (GDN_YEN)	GCNg, GCRg, GENg, GEN_YEN, LPROD, LPRODg, Spread, STN, ULCg, WRNg, YGA, IIPtotg, IIPmang, XTRg, YWRg
84:1 93:4	7	36	1.12	0.76 (Spread)	3.18 (M1g)	GCRg, LPRODg, XTRg, MTRg
85:1 94:4	22	24	1.33	1.01 (PCDg)	2.24 (confind)	LPRODg, ITNg, ITRg, IIPtotg, YWRXg, TFTg
86:1 95:4	34	12	1.80	0.91 (STN)	3.34 (GPN_YEN)	GCRg, LPRODg, WINg
87:1 96:4	6	40	0.93	0.76 (WRNg)	2.97 (CAN)	COMPRg, EERg, LPRODg, Spread, GPN_YEN
88:1 97:4	7	39	0.87	0.70 (GENg)	2.66 (GEN_YEN)	EERg, Spread, GPN_YEN
89:1 98:4	15	31	1.86	0.74 (LN/LF)	7.94 (TFTg)	GEN_YEN, Spread

"g" indicates growth rate of original variable

Table 7: Performance of indicators in forecasting inflation up to four quarters ahead

	Number of Indicators That Performed		RMSE-*h*		
Estimation period	**Better Than AR**	**Worse Than AR**	**AR**	**Best Indicator**	**Worst Indicator**
75:1 84:4	32	6	4.31	1.81 (GDN_YEN)	4.76 (LPROD)
75:1 85:4	8	30	1.42	0.60 (COMPRg)	5.10 (LN/LF)
75:1 86:4	22	16	1.65	0.46 (TFTg)	6.40 (Spread)
75:1 87:4	16	24	0.80	0.25 (LN/LF)	3.51 (EEN)
75:1 88:4	19	21	1.36	0.88 (Spread)	7.78 (GPN_YEN)
75:1 89:4	22	21	1.24	0.82 (EEN)	3.31 (TFTg)
75:1 90:4	14	29	0.85	0.38 (TBR)	2.5 (CAN)
75:1 91:4	11	32	1.68	0.51 (GDN_YEN)	3.19 (M1Ng)
75:1 92:4	14	29	2.06	1.55 (GCNg)	6.86 (MTRg)
75:1 93:4	9	34	0.99	0.54 (GCNg)	5.10 (GDN_YEN)
75:1 94:4	15	31	1.11	0.59 (M1Ng)	2.29 (GDN_YEN)
75:1 95:4	29	17	1.26	0.96 (Spread)	1.76 (GDN_YEN)
75:1 96:4	19	27	1.15	0.57 (PYRg)	3.41 (LN/LF)
75:1 97:4	4	42	0.76	0.69 PPImang	1.91 (IIPmang)
75:1 98:4	36	10	1.52	0.72 (GEN_YEN)	49.65 (M1Ng)
75:1 99:4	30	16	1.41	0.67 (YGA)	2.08 (ULCg)

“g” indicates growth rate of original variable

Table 8: Ranking the Inflation Indicators (4-quarter forecasts)

	Number of Times the Indicator			
	Outperforms Autoregression	**Underperforms Autoregression**	**Produces Best Forecast**	**Produces Worst Forecast**
COMPRg	9	7	1	-
EEN	4	12	-	-
EENg	8	8	-	-
EER	3	13	-	1
EERg	6	10	-	-
FDDg	4	12	-	1
GCNg	8	8	-	-
GCRg	7	9	-	-
GDN_YEN	3	13	1	4
GENg	9	7	1	-
GEN_YEN	7	9	-	-
LN/LF	9	7	2	-
LPROD	3	13	-	2
LPRODg	8	8	-	-
LTN	6	10	1	-
Spread	6	10	2	-
PCDg	11	5	3	-
PCNg	9	7	1	-
PCRg	10	6	-	-
STN	4	12	1	-
ULCg	5	11	-	1
URX	9	7	-	1
WRNg	11	5	2	-
YGA	8	8	-	-
M3Ng	0	16	-	-
CAN	7	9	-	1
GPN_YEN	10	6	-	1
GRN_YEN	6	10	-	-
ITNg	11	5	-	-
ITRg	8	8	-	-
PYRg	9	7	1	-
IIPtotg	3	9	-	-
IIPmang	1	11	-	1
ecsent	3	3	-	-
confind	1	5	-	-
PPImang	4	2	1	-
PPItotg	2	8	-	-
WINg	11	5	-	-
TBR	3	13	1	-
MTRg	6	10	-	1
XTRg	8	8	-	-
YWRg	5	11	-	-
YWRXg	9	7	-	-
GDPg	10	6	-	-
TFTg	8	8	1	1
M1Ng	4	7	1	2

“g” indicates the growth rate of original variable

Table 9: Pooled forecasts for inflation – RMSE-*h* relative to benchmark AR

	***h*=8 recursive**		***h*=4 recursive**	
Estimation period	**Mean**	**Median**	**Mean**	**Median**
75:1 84:4	0.69	0.68	0.72	0.69
75:1 85:4	2.42	2.13	1.76	1.78
75:1 86:4	1.53	0.98	1.19	0.93
75:1 87:4	1.13	0.92	1.36	1.14
75:1 88:4	1.29	1.06	1.21	1.07
75:1 89:4	1.15	1.05	1.15	0.96
75:1 90:4	1.42	1.25	1.31	1.17
75:1 91:4	1.23	1.15	1.22	1.23
75:1 92:4	1.41	1.16	1.23	1.13
75:1 93:4	1.46	1.22	1.45	1.26
75:1 94:4	1.21	1.11	1.14	1.10
75:1 95:4	1.09	1.00	1.00	0.97
75:1 96:4	1.66	1.27	1.26	1.12
75:1 97:4	2.25	1.02	1.41	1.30
75:1 98:4	1.07	0.73	1.54	0.86
75:1 99:4			0.87	0.86

Note to the table: The table reports the RMSE-*h* ratios for 1 to 8 (and 1 to 4) step ahead forecasts of GDP growth using the mean and median of all the single indicators based forecasts, using either recursive or rolling (10 year window) estimated over the period indicated in the first column.

Table 10: Performance of Forecast Feasible Indicators on Forecasting Inflation

	RMSE-*h*=1		**RMSE-*h*=4**		**RMSE-*h*=8**	
Point in time	**AR**	**IND**	**AR**	**IND**	**AR**	**IND**
90:4	0.10	1.23	0.85	2.93	1.08	**0.95**
91:4	0.04	0.77	1.68	**0.48**	1.71	2.01
92:4	3.91	**3.55**	2.06	2.17	1.63	2.31
93:4	1.75	1.75	0.99	**0.69**	1.05	1.17
94:4	1.88	2.36	1.11	**0.70**	1.12	1.26
95:4	1.67	1.71	1.26	**0.81**	1.08	1.17
96:4	0.34	**0.07**	1.15	**0.91**	1.09	1.15
97:4	0.25	1.35	0.76	1.77	0.98	1.33
98:4	0.43	**0.41**	1.52	**1.11**	2.23	**1.69**
99:4	1.55	2.09	1.41	**0.72**		

GDP GROWTH INDICATORS FOR EURO AREA

Table 11: Performance of Indicators in Forecasting GDP Growth Eight Quarters Ahead

	Number of Indicators That Performed			RMSE-*h*		
Estimation period	**Better Than AR**	**Worse Than AR**	**AR**	**Best Indicator**	**Worst Indicator**	***PcGets Deletes***
75:1 84:4	6	32	2.62	2.52 (URX)	166.35 (YGA)	LPRODg, XTRg, TBR, YWRg
75:1 85:4	9	29	3.75	2.90 (PYRg)	26.50 (YGA)	LPROD, LPRODg, XTRg, YWRg, PYRg
75:1 86:4	8	30	3.18	2.96 (GCRg)	49.28 (YGA)	GPN_YEN, MTRg, XTRg, GRN_YEN, ITRg
75:1 87:4	21	19	2.15	1.53 (STN)	287.46 (YGA)	EERg, GEN_YEN, GPN_YEN, PCNg, XTRg, WRNg, ITRg, WINg
75:1 88:4	25	15	1.97	1.42 (LPROD)	6.20 (FDDg)	LPRODg, XTRg, ITRg
75:1 89:4	25	18	1.48	0.99 (YWRXg)	33.15 (YGA)	EERg
75:1 90:4	19	24	2.33	1.53 (TFTg)	17.28 (YGA)	LPRODg
75:1 91:4	19	24	3.49	2.36 (TFTg)	15.54 (YGA)	GPN_YEN, LPRODg, WRNg
75:1 92:4	9	32	2.46	1.71 (IIPtotg)	16.91 (YGA)	EER, EERg, GPN_YEN, XTRg, WRNg, WINg
75:1 93:4	8	35	1.11	0.96 (FDDg)	3.71 (LPROD)	EENg, EER, EERg, GCNg, GCRg, GPN_YEN, XTRg, TBR, ULCg, WRNg
75:1 94:4	4	42	0.97	0.78 (GEN_YEN)	3.58 (Spread)	EENg, EER, EERg, GCNg, GCRg, GPN_YEN, XTRg, TBR, ULCg, WRNg, ITRg, WINg
75:1 95:4	13	33	1.36	1.17 (IIPmang)	13.61 (YGA)	EENg, EER, EERg, GCNg, GCRg, XTRg, TBR, ULCg, WINg
75:1 96:4	5	41	1.48	1.35 (PCNg)	5.71 (YGA)	ITRg, PYRg
75:1 97:4	6	40	1.33	1.18 (COMPRg)	256.89 (TFTg)	XTRg, WRNg
75:1 98:4	22	24	1.28	0.57 (LTN)	691.36 (TFTg)	GPN_YEN, XTRg, WRNg

"g" indicates growth rate of original variable

Table 12: Ranking the GDP Growth Indicators (8-quarter forecasts)

	Number of Times the Indicator				
	Outperforms Autoregression	Underperforms Autoregression	Produces Best Forecast	Produces Worst Forecast	Is Deleted
infl	5	10	-	-	-
CAN	5	10	-	-	-
EEN	4	11	-	-	-
EENg	3	12	-	-	3
EER	4	11	-	-	4
EERg	3	12	-	-	6
FDDg	4	11	1	1	-
GCNg	3	12	-	-	3
GCRg	2	13	1	-	3
GDN_YEN	6	9	-	-	-
GENg	5	10	-	-	-
GEN_YEN	9	6	1	-	1
GPN_YEN	2	13	-	-	7
LNNg	7	8	-	-	-
LN/LF	7	8	-	-	-
LPROD	1	14	1	1	1
LPRODg	2	13	1	-	4
LTN	4	11	1	-	-
Spread	6	9	-	1	-
PCNg	4	11	1	-	1
PCRg	6	9	-	-	-
STN	9	6	1	-	-
MTRg	6	9	-	-	1
XTRg	3	12	-	-	11
TBR	4	11	-	-	4
TFTg	3	12	2	2	-
ULCg	3	12	-	-	3
URX	7	8	1	-	-
WRNg	2	13	-	-	7
YGA	0	15	-	11	-
YWRg	9	6	-	-	2
YWRXg	8	7	-	-	-
M3Ng	2	13	-	-	-
GRN_YEN	5	10	-	-	1
ITNg	5	10	-	-	-
ITRg	5	10	-	-	5
PYRg	5	10	1	-	2
COMPRg	5	10	1	-	-
IIPtotg	7	3	1	-	-
IIPmang	5	5	1	-	-
ecsent	0	5	-	-	-
confind	0	5	-	-	-
PPImang	3	2	-	-	-
PPItotg	3	7	-	-	-
WINg	2	13	-	-	4
M1g	4	6	-	-	-

"g" indicates growth rate of original variable

Table 13: Forecasting performance of selected US variables for EURO GDP growth

	Number of Times the Indicator				
	Outperforms Autoregression	**Underperforms Autoregression**	**Produces Best Forecast**	**Produces Worst Forecast**	**Is Deleted**
GDPg	4	11	-	-	2
ipg	4	11	-	-	6
cap	6	9	-	-	2
lhman	8	7	1 (sample 86)	-	-
lurat	7	8	-	-	1
fsg	8	7	1 (sample 96)	-	-
fy10gov	7	8	-	-	4
fcod	7	8	1 (sample 84)	-	3
Spread10y	4	11	-	-	6
Spread3m	4	11	-	-	3
ereff	2	13	1 (sample 94)	-	4
ereffg	2	13	-	-	3
m2g	4	11	-	-	3
infl	5	10	-	-	2
whetotg	1	14	-	-	9
wcg	6	9	-	-	3
conf	7	8	-	-	4

"g" indicates growth rate of original variable

Table 14: Forecasting performance of US and EURO factors for EURO GDP growth

	Number of Times the Indicator				
	Outperforms Autoregression	**Underperforms Autoregression**	**Produces Best Forecast**	**Produces Worst Forecast**	**Is Deleted**
US-F1	8	7	-	-	-
US-F2	4	11	1 (sample 87)	-	6
US-F3	6	10	-	-	3
US-F4	1	14	-	-	9
US-F5	0	16	-	-	9
US-F6	1	14	-	-	8
EU-F1	2	13	-	-	-
EU-F2	3	12	-	-	2
EU-F3	2	13	1 (sample 95)	-	9
EU-F4	2	13	-	-	6
EU-F5	4	11	-	-	5
EU-F6	3	12	-	-	3

Table 15a: Performance of groups of variables in forecasting inflation up to eight quarters ahead (conservative strategy)

Estimation period	AR	RMSE-*h* Groups 1	2	3	4	5	6	7	8	9	10	Best single
75:1 90:4	1.08	2.42	2.73	**1.89**	2.37	**2.17**	2.37	**1.71**	5.83	**2.32**	**2.22**	1.53
75:1 91:4	1.71	**3.32**	**2.48**	3.58	**3.14**	**2.95**	3.51	5.84	7.84	**3.46**	**3.36**	2.36
75:1 92:4	1.63	**2.41**	**2.43**	**2.00**	**2.00**	**2.19**	2.73	20.71	**2.29**	2.71	2.65	1.71
75:1 93:4	1.05	2.25	3.11	1.61	1.94	1.12	**1.11**	10.15	2.01	1.17	1.54	0.96
75:1 94:4	1.12	2.81	3.65	1.50	2.44	1.55	**0.97**	12.27	1.53	1.25	1.18	0.78
75:1 95:4	1.08	2.13	1.64	1.38	1.39	1.67	**1.35**	7.80	**1.21**	**1.15**	**1.35**	1.17
75:1 96:4	1.09	**1.36**	1.60	1.63	1.63	1.49	1.50	18.93	**1.36**	**1.55**	1.50	1.35
75:1 97:4	0.98	**1.32**	**1.10**	1.85	1.85	1.40	1.35	6.22	**1.32**	**1.28**	**1.28**	1.18
75:1 98:4	2.23	1.46	**1.08**	**0.96**	**0.74**	**0.92**	1.29	4.40	1.44	**1.00**	1.47	0.57

BOLD indicates that the corresponding RMSE-*h* is smaller than the RMSE-*h* of the pure AR model.

Table 15b: Performance of groups of variables in forecasting inflation up to eight quarters ahead (liberal strategy)

Estimation period	AR	RMSE-*h* Groups 1	2	3	4	5	6	7	8	9	10	Best single
75:1 90:4	1.08	5.80	**1.73**	4.10	4.84	**2.17**	3.19	10.21	5.30	**2.25**	4.99	1.53
75:1 91:4	1.71	6.48	**2.48**	**2.13**	7.04	**2.95**	4.38	3.53	20.25	**3.45**	**3.39**	2.36
75:1 92:4	1.63	4.71	**2.43**	**1.74**	3.78	**2.08**	2.52	36.41	3.23	3.02	**1.71**	1.71
75:1 93:4	1.05	4.90	3.11	1.62	9.31	1.14	2.38	18.45	5.34	1.89	1.72	0.96
75:1 94:4	1.12	2.81	3.65	1.14	2.31	1.35	3.10	10.35	1.53	2.75	1.07	0.78
75:1 95:4	1.08	2.42	1.65	1.42	1.42	1.67	**1.33**	29.27	2.94	3.01	**1.25**	1.17
75:1 96:4	1.09	2.51	1.59	1.88	1.59	1.67	2.56	16.95	3.06	1.49	1.67	1.35
75:1 97:4	0.98	**1.32**	**1.12**	1.92	1.84	1.34	2.32	6.69	4.54	1.38	1.39	1.18
75:1 98:4	2.23	1.45	**1.03**	1.37	1.31	**0.92**	**1.14**	3.48	1.78	1.47	1.42	0.57

BOLD indicates that the corresponding RMSE-*h* is smaller than the RMSE-*h* of the pure AR model.

Table 15c: Groupings

Gr 1	Gr 2	Gr 3	Gr 4	Gr 5	Gr6	Gr7	Gr8	Gr9	Gr10
GEN_YEN	COMPRg	GEN_YEN	GEN_YEN	GEN_YEN	US factors	EURO factors	GEN_YEN	lhman	GEN_YEN
STN	EENg	LNNg	LNNg	STN			STN	lurat	STN
YWRg	EERg	LN/LF	LN/LF	IIPtotg			IIPtotg	fsg	IIPtotg
YWRXg	Spread	URX	STN				US F1	fy10gov	lhman
IIPtotG	WRNg	YWRg	URX				US F2	fcod	lurat
	ULCg	YWRXg	YWRg				US F3	conf	fsg
		IIPtotG	YWRXg				EU F2		fy10gov
			IIPtotG				EU F5		fcod
							EU F6		conf

"g" indicates growth rate of original variable

Group 1 – Indicators outperforming the autoregression at least 50% of times (5 variables)
Group 2 – Financial indicators and prices
Group 3 – Best real variables from Table 13
Group 4 – Best 8 variables from Table 13
Group 5 – Best 3 variables from Table 13 (without world)
Group 6 – 6 US factors
Group 7 – 6 EURO factors
Group 8 – Best 3 variables from Table 13 (without world) + best factors from Table 15
Group 9 – Best 6 US variables
Group 10 – Best 3 variables from Table 13 (without world) + best 6 US variables from Table 16

Table 16: Performance of Indicators in Forecasting GDP Growth Eight Quarters Ahead, 10-year rolling window

Estimation period	Number of Indicators That Performed Better Than AR	Number of Indicators That Performed Worse Than AR	RMSE-*h* AR	RMSE-*h* Best Indicator	RMSE-*h* Worst Indicator	***PcGets Deletes***
75:1 84:4	6	32	2.62	2.52 (URX)	166.35 (YGA)	LPRODg, XTRg, TBR, YWRg
76:1 85:4	10	28	3.72	3.25 (GENg)	31.25 (YGA)	
77:1 86:4	15	23	3.05	2.19 (TFTg)	94.96 (YGA)	EER, EERg, FDDg, GCNg, GPN_YEN, MTRg, XTRg, ULCg, WRNg, YWRXg, ITRg, WINg
78:1 87:4	21	19	2.18	1.18 (GRN_YEN)	15.65 (LPROD)	EEN, EENg, EER, EERg, FDDg, GEN_YEN, MTRg, XTRg, TBR, YWRXg, ITNg, ITRg
79:1 88:4	20	20	2.04	1.53 (GRN_YEN)	61.27 (FDDg)	EEN, EENg, EER, GCRg, GPN_YEN, ITR, LNNg, LPRODg, XTRg, YWRXg, ITNg, ITRg
80:1 89:4	5	38	1.31	1.17 (IIPtotg)	10.39 (YGA)	EEN, EENg, EERg, GCRg, LNNg, LPRODg, PCRg, MTRg, XTRg, ITRg, PYRg
81:1 90:4	15	28	2.34	1.57 (TFTg)	237.40 (YGA)	EENg, EERg, GCRg, LPRODg, Spread, XTRg, TBR, PYRg
82:1 91:4	13	30	3.52	1.27 (YGA)	10.18 (FDDg)	EENg, EERg, GCRg, LPRODg, Spread, XTRg, TBR, M3Ng, PYRg, COMPRg
83:1 92:4	7	36	2.32	1.76 (TBR)	313.75 (YGA)	infl, EENg, EERg, FDDg, GCRg, Spread, PYRg, COMPRg
84:1 93:4	0	43	1.11	-	250.34 (YGA)	CONSTANTS, PYRg, COMPRg
85:1 94:4	21	25	1.35	0.95 (GEN_YEN)	16.73 (TFTg)	
86:1 95:4	7	39	1.33	1.08 (YWRg)	9.78 (YGA)	
87:1 96:4	1	45	1.47	1.46 (GDN_YEN)	38.74 (YGA)	GCRg, YWRXg
88:1 97:4	6	40	1.40	1.03 (STN)	295.67 (TFTg)	infl, FDDg, GCNg, GCRg, LN/LF, Spread, PCNg, PCRg, MTRgM XTRg, YWRXg, COMPRg, PPImang, PPItotg
89:1 98:4	13	33	1.53	0.67 (LNNg)	438.54 (TFTg)	Spread, PCRg, COMPRg, PPImang, PPItotg

“g” indicates growth rate of original variable

Table 17: Performance of Indicators in Forecasting GDP Growth Four Quarters Ahead

	Number of Indicators That Performed		RMSE-*h*		
Estimation period	**Better Than AR**	**Worse Than AR**	**AR**	**Best Indicator**	**Worst Indicator**
75:1 84:4	6	32	1.46	1.19 (LTN)	17.43 (YGA)
75:1 85:4	11	27	3.40	3.05 (GEN_YEN)	4.68 (YGA)
75:1 86:4	3	35	4.05	3.53 (GCRg)	7.65 (YGA)
75:1 87:4	23	17	1.10	0.92 (STN)	30.11 (YGA)
75:1 88:4	26	14	2.26	1.50 (LPROD)	6.28 (FDDg)
75:1 89:4	28	15	1.91	1.09 (MTRg)	5.65 (YGA)
75:1 90:4	12	31	0.90	0.47 (Spread)	4.46 (M1Ng)
75:1 91:4	22	21	3.17	2.00 (TFTg)	4.87 (URX)
75:1 92:4	14	29	3.31	1.75 (TFTg)	5.67 (ITNg)
75:1 93:4	13	30	1.15	0.37 (IIPmang)	4.47 (LPROD)
75:1 94:4	11	32	1.15	0.35 (YGA)	4.03 (Spread)
75:1 95:4	10	36	0.73	0.56 (LNNg)	2.79 (STN)
75:1 96:4	12	32	1.73	1.38 (YGA)	2.99 (CAN)
75:1 97:4	11	35	1.17	1.00 (TFTg)	3.72 (LPROD)
75:1 98:4	26	20	1.55	0.72 (LTN)	508.95 (TFTg)
75:1 99.4	8	38	0.78	0.57 (ITNg)	2.05 (IIPmang)

“g” indicates growth rate of original variable

Table 18: Ranking the GDP Growth Indicators (4-quarter forecasts)

	Number of Times the Indicator			
	Outperforms Autoregression	**Underperforms Autoregression**	**Produces Best Forecast**	**Produces Worst Forecast**
infl	7	9	-	-
CAN	7	9	-	1
EEN	6	10	-	-
EENg	6	10	-	-
EER	6	10	-	-
EERg	5	11	-	-
FDDg	5	11	-	1
GCNg	5	11	-	-
GCRg	4	12	1	-
GDN_YEN	7	9	-	-
GENg	4	12	-	-
GEN_YEN	7	9	1	-
GPN_YEN	4	12	-	-
LNNg	7	9	-	-
LN/LF	5	11	-	-
LPROD	3	13	1	2
LPRODg	3	13	-	-
LTN	6	10	2	-
Spread	6	10	1	1
PCNg	4	12	-	-
PCRg	6	10	-	-
STN	9	7	1	1
MTRg	4	12	1	-
XTRg	3	13	-	-
TBR	4	12	-	-
TFTg	7	9	3	1
ULCg	4	12	-	-
URX	7	9	-	1
WRNg	2	14	2	5
YGA	4	11	-	-
YWRg	8	8	-	-
YWRXg	0	16	-	-
M3Ng	0	16	-	-
GRN_YEN	5	11	-	-
ITNg	5	11	1	1
ITRg	3	13	-	-
PYRg	7	9	-	-
COMPRg	8	8	-	-
IIPtotg	8	5	-	-
IIPmang	6	7	1	1
ecsent	1	5	-	-
confind	0	6	-	-
PPImang	2	4	-	-
PPItotg	6	5	-	-
WINg	3	13	-	-
M1g	4	7	-	1

"g" indicates growth rate of original variable

Table 19: Pooled forecasts for GDP growth – RMSE-*h* relative to benchmark AR

	***h*=8 recursive**		***h*=4 recursive**	
Estimation period	**Mean**	**Median**	**Mean**	**Median**
75:1 84:4	2.76	1.09	1.58	1.17
75:1 85:4	1.22	1.05	1.04	1.01
75:1 86:4	1.55	1.05	1.12	1.08
75:1 87:4	4.71	0.97	2.97	1.70
75:1 88:4	1.08	0.96	1.00	0.93
75:1 89:4	1.54	0.97	0.97	0.88
75:1 90:4	1.23	1.00	1.50	1.30
75:1 91:4	1.11	1.00	1.01	1.00
75:1 92:4	1.22	1.06	1.05	1.02
75:1 93:4	1.31	1.02	1.14	1.00
75:1 94:4	1.43	1.07	1.27	1.01
75:1 95:4	1.34	1.00	1.47	1.05
75:1 96:4	1.23	1.05	1.07	1.03
75:1 97:4	5.58	1.02	1.34	1.11
75:1 98:4	12.80	1.00	8.05	0.97
75:1 99:4			1.32	1.20

Note to the table: The table reports the RMSE-*h* ratios for 1 to 8 (and 1 to 4) step ahead forecasts of GDP growth using the mean and median of all the single indicators based forecasts, using either recursive or rolling (10 year window) estimated over the period indicated in the first column.

Table 20: Performance of Forecast Feasible Indicators on Forecasting GDP Growth

	RMSE-*h*=1		**RMSE-*h*=4**		**RMSE-*h*=8**	
Point in time	**AR**	**IND**	**AR**	**IND**	**AR**	**IND**
90:4	0.18	**0.13**	0.90	2.57	2.33	4.27
91:4	2.05	**1.17**	3.17	3.33	3.49	**3.49**
92:4	6.42	**4.87**	3.31	**2.50**	2.46	3.67
93:4	0.16	0.24	1.15	4.70	1.11	7.26
94:4	0.43	0.58	1.15	10.3	0.97	1.00
95:4	0.52	**0.27**	0.73	**0.64**	1.36	**1.35**
96:4	0.91	4.13	1.73	**1.71**	1.48	1.56
97:4	1.35	**0.75**	1.17	**1.14**	1.33	1.62
98:4	1.48	**1.20**	1.55	2.19	1.28	**1.24**
99:4	1.13	**0.96**	0.78	1.80		