Diffusion index-based inflation forecasts for the euro area[1]

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1. Introduction

One important development over the last few years has been the steadily growing flow of information accruing to the economist, with data becoming increasingly available at a higher degree of disaggregation, at the regional, temporal and sectoral levels. The availability of such new information has boosted economic analysis in directions other than the traditional economy-wide macroeconomic approach, such as firm-level, panel or high-frequency data analysis. However, macroeconomics could also profit from this richer environment, and work along these lines is nowadays a priority. This is the case for every economy for which sufficiently detailed data exist, but also applies to a particular extent to the euro area. One way to circumvent the relative scarcity of data covering a long period of time for the euro area is to use as much data as are available for all of the member countries. In stark contrast with the area as a whole, most member countries have a long and well established tradition of collecting a broad range of data, for which long time series are therefore available. It is thus particularly important for the analysis of euro area data to explore new techniques or adapt old ones, which would enable the economists to exploit large amounts of country data with only a partial geographic coverage of the area. This paper examines one of these new techniques, with a view to analysing the links between country data of the most diverse nature and a variable of primary interest to the ECB, namely area-wide inflation.

In a recent and influential paper, Stock and Watson (1998) initiated an interesting line of research by proposing the use of dynamic factors - extracted according to their own specific methodology - as potential indicator variables for future inflation. Further, the same authors thoroughly analysed the relative forecasting performance of such factors (see Stock and Watson [1999]) with results that, although far from conclusive, are at least promising. The proposed methodology falls within the dynamic factor analysis in line with research going back to Sargent and Sims (1977) or Quah and Sargent (1993) and continued in recent papers such as Forni and Reichlin (1998), Forni et al (1999) and Forni and Lippi (2000). The approach advocated by Stock and Watson (1998) is being applied in a number of related studies, examples of which for the euro area are Marcellino et al (2000) and a companion paper to this one (see Angelini et al [2001]). In the latter paper, factors are extracted from a large dataset of EMU country-level measures of prices with a view to summarising trend inflation in the euro area as a limited number of indicators.

The main goal pursued in this paper and its companion is to assess ways in which the very rich set of data available for the 11 EMU countries (12 since early 2001) can be exploited for the benefit of the common monetary policy. In a sense, and bearing in mind the obvious differences, the euro area faces a situation akin to that faced by a country with extensive, high-quality regional data. One possible way to exploit this wealth of data is by directly addressing analyses and forecasts at the country level, to be aggregated afterwards at the area-wide level, the so-called “bottom-up” approach to forecasting. Another approach, assessed in this paper and not necessarily at odds with the previous one, is to explore ways to summarise the country information at the area-wide level as a greatly reduced number of series with similar information content, thus exploiting country information without losing sight of the area-wide perspective.

1 Opinions expressed in the paper are those of the authors and do not necessarily reflect those of the ECB. This paper, in an earlier version, was presented at a BIS workshop on Empirical Studies of Structural Changes and Inflation in October 2000. The authors are grateful to the BIS for hosting the workshop, and to the discussant of the paper, J Ihrig of the Federal Reserve Board, and attendees of the workshop for useful comments. We also greatly benefited from discussions with J Stock at various stages of this work as well as from input from colleagues at the ECB and an anonymous referee. Remaining errors are the sole responsibility of the authors.

The current paper goes beyond our previous work in three respects. First, the extracted factors are systematically analysed along a dimension which was only marginally addressed previously, ie their ability to forecast inflation. Second, factors associated with non-price variables also receive a great deal of attention in the following, whereas the companion paper is restricted to factors derived from nominal variables. Finally, a thorough account of the basic in-sample properties of the factors is given here with more description and detail than before.

The paper is structured as follows. Section 2 briefly recalls the technical background of the factor extraction procedures, and discusses a number of practical problems found in this process. Resulting factors are then described in Section 3. Section 4 gives details on the forecasting exercise performed, in terms of both the tools (ie the “models” assumed to hold) and the tests for forecasting ability. Section 5 presents and comments on the results. Section 6 concludes.

2. Factor extraction

At this point, it is worth highlighting some technical aspects of the approach.[2] The method uses principal-component analysis to extract information from large macroeconomic datasets. Initial raw data are present in the form of a large number of variables related to the euro area, from which common factors are extracted following standard statistical procedures in a non-standard framework. The analysis starts with a dataset, of possibly large dimension, containing raw variables assumed to be generated by a small number of common factors, as represented by variable x_t in expression (1.1).[3] Variable x_t is a column-vector representation of N different variables for period t, the total number of observations being T. In the expression, x_t is an N-column vector, f_t is an r-column vector (the factors) and Λ is a matrix with N columns and r rows (the loadings). Variable ε_t is an error process whose variance depends on the variance of the $N\text{-}r$ factors missing in the expression. If all the variables indexed by t are stacked for the T periods of the sample, expression (1.2) results, in which stacked variables appear in upper case.

$$x_t = f_t \cdot \Lambda + \varepsilon_t, \quad t = 1,...,T \tag{1.1}$$

$$X = F \cdot \Lambda + \mathrm{E} \tag{1.2}$$

Factors in (1.2) have to be uncorrelated among themselves and with the residual E (ie ε_t in stacked form), and must be such that the variance of the residual is minimised. As shown by Stock and Watson (1998), under fairly general conditions the factors can be estimated - up to a rotation matrix - by a standard principal-component analysis based on the NxN cross-moments matrix $X'X$ or alternatively on the TxT matrix XX'. As is standard, there is a one-to-one mapping - again up to a rotation matrix - between the two approaches, the preferred one being based on the relative size of the two dimensions. In the dataset analysed below the latter approach is taken, as its time dimension is smaller than the variable dimension. One key decision in the analysis is the number of factors that have to be extracted, which can range from 1 to (in the present case) T. Although some methods have recently been proposed in the literature to test and choose the underlying number of factors (see, for example, Bai and Ng [2000]), the approach followed in this paper has been simpler. Forecasting tests have been performed with alternative numbers of factors, with an upper limit in their number imposed not by the econometrician but by the quality of the estimated factors in terms of variance explained and also their robustness to missing observations.

One advantage of this approach is the possibility of using expanded sets of information in deriving the factors, ie the possibility of using information from variables that do not cover the whole period in order to fine-tune the estimation of the factors. Variables that are not present for some periods (ie variables with *missing values* for part of the sample) can nevertheless be used to extract factors, thanks to a

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2 For a more detailed discussion, the reader is referred to Stock and Watson (1998) or, for a less technical description, to Angelini et al (2001).

3 Lags of the factors can enter (1.1) without loss of generality. Mild time variation in Λ is also possible.

slightly more complex factor estimation procedure, as shown by Stock and Watson (1988). The principal-component approach described in the previous paragraph, and the corresponding matrix decomposition problem, are only valid in the presence of complete datasets, ie datasets in which no data are missing (a situation termed as *balanced panel*). Stock and Watson (1988) show that maximising the likelihood of the system (1.2) in the case of a balanced panel results in a standard matrix decomposition problem, but they also prove that it is still possible to perform the estimation in the presence of incomplete information using the well known EM algorithm. In this case, the system (1.2) itself can be used to derive expected values of missing variables (the E step), which can then be used to maximise the system (the M step). The final estimates result from iterations on these two steps until final convergence. It is obviously necessary to provide initial estimates of the parameters for the first iteration. Following a proposal made by the two authors, the initial factors will be given by the larger dataset covering the full sample with no missing data, ie the largest subset of the original dataset providing a balanced panel.[4]

Given the situation for euro area data, characterised by missing observations for a number of countries, it is important to understand the process by which the EM algorithm can be applied to unbalanced panels. Starting from some initial estimates, $\hat{F}$ of the factors and $\hat{\Lambda}$ of the loadings, an estimate of the complete dataset is obtained by replacing missing values in x_t with corresponding elements of $\hat{x}_t = \hat{\Lambda} \cdot \hat{F}$. A corresponding cross-moments matrix can be formed from the generated variables, and factors and loadings re-estimated. Each time an iteration is run, new factors are extracted and used in the following iteration. One important aspect of this algorithm is that iterations can be made taking *all* eigenvalues of the matrix, or selecting only those most significant. Although both approaches provide asymptotically correct estimates of the true factors, the small-sample properties could differ markedly. In the case in question, this may have had an important impact on the calculations.

Data used in this paper relate to the 11 countries of the area that were taken into consideration (ie members before 2001) and cover a broad array of economic items. The rather large dataset comprises 278 variables spanning the period from (roughly) 1977 to 1999. A fuller description of the variables, with a breakdown by country, is provided in Appendix C. Most series are of quarterly frequency, and those present at monthly frequency were transformed into the lower frequency, because of the lack of monthly data for many series used and also the sensitivity of the results to missing observations when the latter become too numerous, as described below. One notable feature of the series is the presence of nominal and real variables in the dataset from which factors were extracted, which raises the possibility of separating purely nominal factors from other influences affecting inflation. This is a desirable feature. The analysis has thus proceeded with two different sets of dynamic factors: first, those extracted from purely nominal information (ie deflators, wages and prices contained in the original database) and, second, all-encompassing dynamic factors as obtained from the complete dataset. Furthermore, some interesting facts were discovered regarding factors extracted from a dataset comprising all the variables except those used for the nominal-only factor extraction. The three sets of factors will be discussed, with a special emphasis on factors extracted from the all-encompassing dataset.

Original series were firstly checked for the presence of outliers and then transformed to get rid of non-stationarity and heteroskedasticity, by taking logs or ratios of variables and differencing the series appropriately. Further to that, all series were standardised by removing their mean and dividing them by their standard error. Factors extracted from the complete dataset will be termed “overall factors”, those extracted from a dataset comprising only prices will correspondingly be termed “nominal factors” and those extracted from non-price variables “non-nominal factors”. As mentioned earlier, nominal factors are already extensively analysed in the companion paper; see Angelini et al (2001).

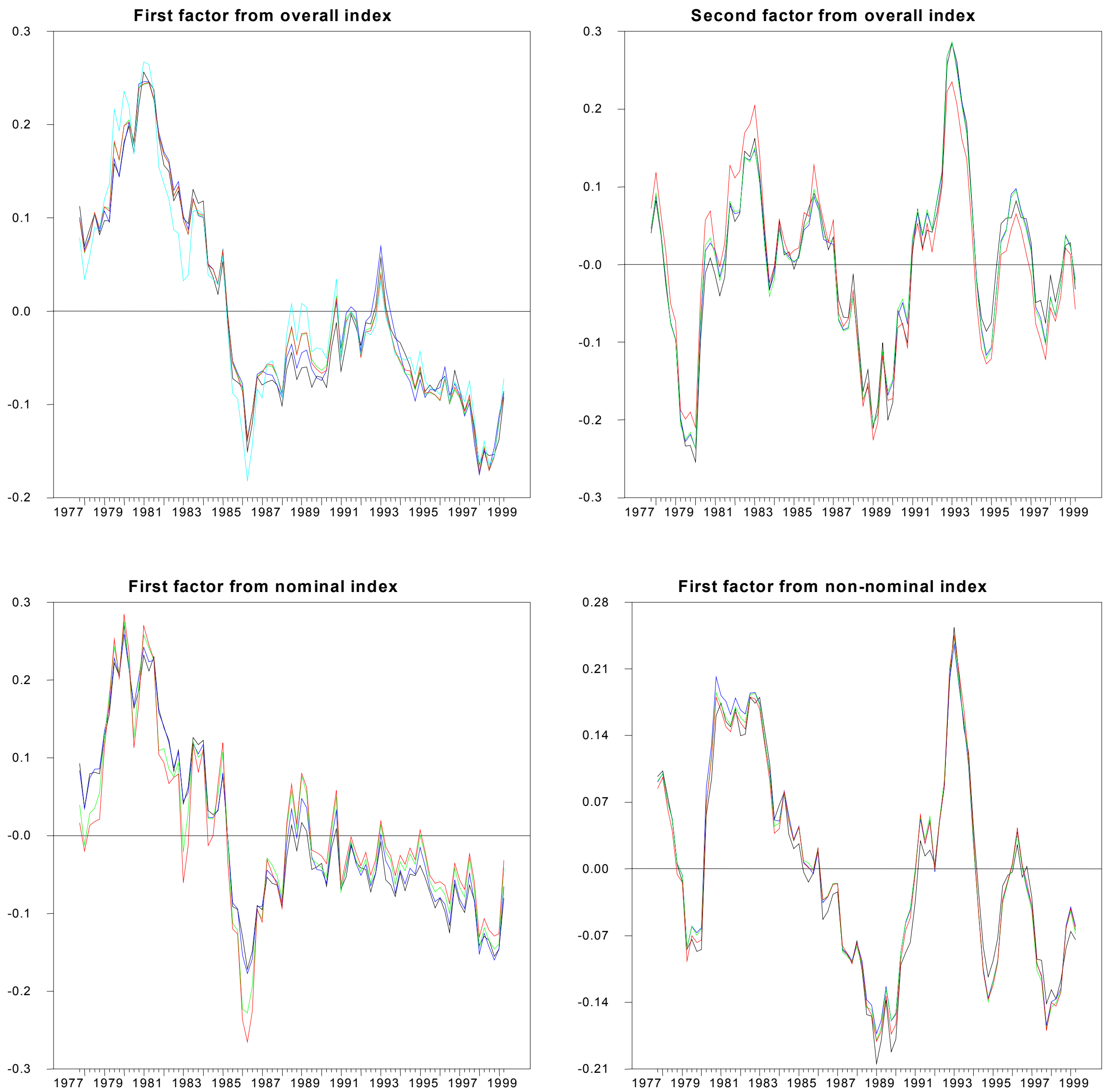
As documented and discussed in detail in Angelini et al (2001), a number of numerical problems appear when estimating factors from an unbalanced panel. Distortion in the final estimates can be present and unbalanced-panel factors can differ considerably from balanced-panel ones and end up being much less plausible. When the number of factors selected in each EM iteration (see above) is

[4] Other options are available which are worth exploring, due to the high likelihood of the last observation being sparse. This paper does not explore these alternatives, but this is an item on our agenda.

relatively large (higher than three or four in our case), numerical problems can be found in the estimation. In the present case, a closer inspection of results highlighted a couple of interesting points. First, the degradation of results in unbalanced-panel estimation is not gradual but increases visibly when more than three or four factors are used. Second, this is especially the case for the "nominal factors", for which results are affected as soon as four factors are computed.[5] In turn, "overall factors" remain plausible when computed with the unbalanced panel until up to five factors are taken into account in the EM algorithm. Finally, "nominal factors" were significantly different when using balanced- or unbalanced-panel estimation, while "overall factors" were much more robust to the inclusion of series with missing observations.

Graph 1

Comparison of factors



5 Additional information, including graphs, regarding the unbalanced-panel distortion with five factors may be found in the companion paper.

A graphic representation of the "overall factors" is shown in Graph 1. The upper left-hand panel shows the first "overall factor" for all estimations, ie for the balanced panel and the unbalanced panel with one-, two-, three- and four-factor EM iterations respectively. The upper right-hand panel shows correspondingly the second "overall factor" for the balanced panel and the unbalanced panel with two- three- or four-factor estimation respectively. (Obviously, no second factor was extracted in one-factor unbalanced-panel estimates.) Although not reported, the "nominal factors" also showed some (lesser) degree of stability across models, with the exception that at most three-factor EM iterations were acceptable instead of four-factor estimations. Beyond this number (ie for EM iterations taking four or more factors) results were clearly unsatisfactory.

The two lower panels of Graph 1 depict another interesting fact about these estimates. They show the first "nominal factor" and the first "non-nominal" factor, to be compared with the "overall factors" of the upper panels. Results clearly point to very different factors according to the information used to extract them. On the other hand, the first "overall factor" is visibly similar to the first "nominal factor", while the second "overall factor" looks very much like the first "non-nominal factor". Very probably, there is a clear separation between "nominal" and "non-nominal" factors in the dataset used. Although it is true that the estimated factors can be rotated, the features just described seem to be able to withstand any possible rotation (as a matter of fact, finding criteria to rotate the factors in a homogenous way would seem a desirable development of the technique.)[6]

3. Analysis of extracted factors

Factors extracted following the aforementioned methodology may serve many different purposes. It has become standard in the literature to assume that they correctly summarise the economy the initial variables refer to, and thus may be a good indicator of important forces underlying the economy. In particular, it has been put forward that these factors may provide good leading-indicator properties and may thus show good forecasting ability (see Stock and Watson [1999]). The main aim of this paper is to test this specific feature of the estimated factors, both the "nominal" and the "overall" ones. It is nevertheless necessary to first give a broad overview of the basic features of the factors obtained, in terms of both their shape and their relationship with the original variables.

Probably the most notable feature of the three sets of factors (ie overall, nominal and non-nominal factors) is the striking similarity of pattern between, respectively, the first "overall" and the first "nominal" factors, and also the second "overall" and the first "non-nominal" factors, as already seen in Graph 1.

Another interesting feature is the lower percentage of the variance explained by the first few factors in the "overall" case: while the first "nominal factor" explained 59% of the variance of prices, the first "overall factor" only explains about 25% of the corresponding data variance. Not surprisingly, the first - ie most important - "non-nominal factor" also explains only a tiny fraction of data variance, thus giving clear indications that the variance in the nominal dataset is highly concentrated around a small number of factors, whereas the non-price system of variables seems to be of a more intricate nature.[7]

Links between factors and variables are also a relevant piece of information, which can be best analysed using the estimated loadings. The latter express the projection of the factors onto the variables, variable Λ in expression (1.1). With a convenient rescaling of the factors, the loadings must lie between -1 and 1, thus giving a direct and easily readable measure of how well the projection for each variable fits. In fact, loadings give a measure of the correlation between factors and each variable since both factors and variables have been normalised beforehand and thus have unit variance. Further, the fact that factors are uncorrelated means that loadings squared can be read as R-squared measures of the regression of individual factors on each variable. Tables 1 and 2 in

6 All the graphs show the factors estimated with the full sample. Factors were estimated recursively in the course of the forecasting test and found to be relatively stable when increasing the estimation sample.

7 As the dataset termed as non-nominal comprises variables usually treated as nominal - foremost among them, money - it is not possible to assign this complexity only to real-activity variables.

Appendix A show the loadings and their squares for all the variables, distinguishing between variables in the balanced panel and those entering only the unbalanced panel.[8]

A quick overview of the tables in Appendix A leads to a number of general conclusions. To begin with, the first "overall factor" is very similar to the first "nominal factor" also in view of the loadings.[9] The table indeed confirms that most, if not all, price variables are strongly correlated with this factor. Other variables with a significant relationship with this factor are earnings, employment and unemployment series, most notably the unemployment rate. More striking is the fact that survey variables related to manufacturing also show a visible degree of correlation: capacity utilisation, order book commands, new orders or stocks in manufacturing firms. The rest of the variables are clearly less related to this factor, most notably GDP and monetary aggregates.

In general terms, the second "overall factor" is much less correlated with variables, although capacity utilisation, survey-based manufacturing series, earnings, employment and unemployment show a relatively sizeable degree of correlation with it. In fact, these series share some degree of correlation with *both* factors. Another interesting point is the relatively high correlation between the second factor and the short- and long-term interest rates, which on the other hand are not strongly correlated with the first factor. Variables belonging to the expenditure side of national accounts do not show a clear-cut correlation pattern with any factor, ie GDP, private consumer expenditure, exports or imports, nor do retail sales variables.

Regarding unbalanced-panel estimates, caution is needed in interpreting them because of the somewhat more complex estimation method used. Caution is particularly needed for the third factor, for which there is evidence of increasing distortion. Nevertheless, there is evidence that the first "overall factor" is still correlated with price variables, although evidence is less compelling than in the balanced panel. For the other variables and factors, it is more difficult to extract unambiguous conclusions.

Last but not least, country-specific evidence is not strong. Most countries show specific correlation patterns for a few variables, but not as a general feature. Finland is probably the clearest case of a general specificity. All in all, correlation patterns along variables are stronger, or at least more visible than along the country dimension.

4. Forecasts

As mentioned above, the backbone of the analysis herein is an exploration of the inflation forecasting ability of factors, with particular emphasis on the euro area. In line with previous and related studies, the current section presents a discussion of the specific forecasting techniques that are to be used for the exercise.

Three preliminary steps need to be covered before going further. It is first of all necessary to spell out clearly what the real-life problem is that one is expected to face. In our case, the main focus is on how to forecast the inflation rate of the euro area. Secondly, it is also important to describe (and to try to approach in the analysis) the real circumstances in which the actual forecast may take place. Regrettably, real-life forecasts based on dynamic factors are difficult to replicate ex post: they usually involve large amounts of data, much of which are provided with lags and delays and are also likely to be revised subsequently. The framework of our analysis will be simpler than the real-life task in that a final, fully revised dataset will be used, but some degree of realism will be achieved by performing true out-of-sample forecasts based on this dataset. As a third and final step, it is important (although maybe less critical) to set the general technical procedures that might be followed to perform the forecasts themselves. Most forecasts embody a lot of discussion among participants with heterogeneous backgrounds and views, and probably will include some degree of judgment. The analysis in this paper, on the other hand, is restricted to automatic and simple procedures, which

8 For those variables entering both the balanced- and the unbalanced-panel estimation, corresponding loadings were very similar.

9 Loadings for the "nominal factors", in a format similar to Table 1, can be found in Angelini et al (2001).

cannot reflect a more protracted and complex forecasting process. The strength of the analysis will lie rather in the many replications of simulated out-of-sample forecasts and their comparison with a predefined benchmark forecasting tool or model, in the belief that procedures able to consistently beat the benchmark are worth developing further. In this, we follow an entirely standard approach within the literature (see Stock and Watson [1999]).

In line with the stated goals, the forecasting exercises are performed on three alternative measures of the euro area inflation rate: the harmonised index of consumer prices (HICP), the consumption deflator and the GDP deflator of the ESA95 euro area national accounts. Data limitations prevent the use of raw data, as they cover only a relatively short amount of time, and necessitate some pre-treatment of the data: the three series were backdated with data from the OECD.[10] Moreover, it was decided to focus on quarterly forecasts due to the quarterly nature of the last two variables, but also because of the much richer set of quarterly series that were available for extracting the factors. Last but not least, the aforementioned problems with unbalanced-panel estimations militated against carrying out the analysis at the higher frequency. Obviously, this is a limitation of the analysis that has to be remedied as soon as possible, for example by collecting as much monthly data for the euro area member states as are available.

As stated, no attempt was made to replicate true forecast circumstances, as for the time being it is prohibitively expensive to prepare a real-time dataset with an accurate representation of the real state of information at each point in time. As has become standard in most of the related literature, the way to approximate this situation has been to use a single final (ie fully revised) dataset covering the whole period, but performing rigorous out-of-sample forecasts using no information belonging to periods later than that at which the forecast is assumed to take place.[11]

The simple techniques followed to derive the forecasts are also fairly standard. A growing body of literature has recently been performing thorough testing exercises on the forecasting ability of sets of variables by running regressions based on (4.1), in which y_t is the variable of interest, assumed to be I(1), z_t is the indicator variable being tested, assumed to be I(0), and ε_t a well behaved error term. In the expression, h stands for the number of periods ahead for which the forecast has to be performed. This expression assumes that there exists a direct mapping from I(0) variables known today to information h-periods ahead. Interestingly, all information required to make the forecast is assumed to be already available, and thus describes a system in which no recursion is needed in order to obtain the forecast.

$$\frac{y_{t+h} - y_t}{h} = A(L) \cdot \Delta y_t + B(L) \cdot z_t + \varepsilon_t \tag{4.1}$$

Expression (4.1) is not the standard approach taken to model dynamic systems outside this brand of literature. Normal procedure is to assume that a one-step-ahead recursive system such as (4.2) applies. This equation seems to be preferable to (4.1) as it apparently uses more information, but this is misleading because our main interest is in deriving forecasts h-periods ahead based on factual data. Equation (4.2) provides such a forecast by recursively generating the periods in between, and thus adds no new information.

$$\Delta y_{t+1} = A(L) \cdot \Delta y_t + B(L) \cdot z_t + \varepsilon_t \tag{4.2}$$

Although (4.1) is nowadays customarily used to make out-of-sample forecasts (see, for example, Stock and Watson [1999], Bernanke [2000] or Marcellino et al [2000]), it is worthwhile exploring the actual differences between the two expressions. Such a step has, to the best of our knowledge, strangely enough been skipped in the factor forecast literature, although, in view of the standard

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10 See the discussion in Angelini et al (2001) and references therein.

11 Bernanke (2000) argues that gains in the analysis from dealing with a true real-time dataset may be smaller than previously thought. It may be worthwhile, nevertheless, to at least replicate in a more realistic setting the true-life exercise by performing Monte Carlo simulations with fake revisions of data known to be revised, a task left for further research.

practices of professional forecasters, the lack of explicit discussion on this difference could cast doubts on the results obtained. Indeed, most professional forecasters would, if they had to forecast variable y_{t+h}, spend a great deal of time considering the expected evolution of z_t, and its impact on y_{t+h}. Thus, they would naturally prefer a forecasting framework described by (4.2). This framework is, however, at odds with the philosophy of dynamic-factor forecasting, precisely because there is in principle not much to be said on the future evolution of the factors. A thorough analysis of the relative forecasting performance of the two approaches is thus warranted. A description of an analysis along these lines is reported in Appendix B, in which the conclusion is reached that for the sample used it is likely that both systems have similar performance.

5. Results

Once the factors have been extracted and the forecasting equations chosen, practical decisions remain to be tackled, such as which variables to forecast, or what indicators to use as benchmarks against which to compare the performance of the dynamic factors. Another practical matter relates to the choice of lags in the forecasting equation, as this was left undefined in the previous section. Finally, it is necessary to set the number of periods ahead that will be tested, and the break date after which the out-of-sample exercises will begin.

As already stated, the basic aim of the paper is to measure accuracy in performing (simple) inflation forecasts. Recall that three variables were retained as measures of inflation: the euro area-wide harmonised index of consumer prices (HICP), the euro area private consumption deflator and the corresponding GDP deflator. The three indexes were treated as I(1) variables, resulting in an assumed I(0) inflation rate. Indicators retained included the "overall", "nominal" and "non-nominal" factors from the balanced panel and the unbalanced panel with one-, two- and three-factor extraction. Alternative indicators employed to forecast euro area inflation were: the euro area unemployment rate, GDP growth, the output gap in the form of a Hodrick-Prescott-filtered GDP, and growth of nominal M3.[12] Both the factors and the output gap were extracted in real-time-like manner, ie were calculated anew each time the starting date for the out-of-sample exercise was changed. The rest of the indicators (ie the unemployment rate and output growth) came from a final database and were thus simply extracted from it after dropping the unneeded observations beyond the starting date of the out-of-sample test.

Contrary to the rest of the indicators, dynamic-factor equations could contain more than one indicator variable, as sometimes more than one factor is used. The simplest equation employed contains only the first factor of the "overall", "nominal" or "non-nominal" datasets. Additional factors are added sequentially, first the second factor added to the first one, and then finally the third one added to the other two. To ensure consistency, unbalanced-panel factors appearing in an equation are always derived from the same underlying estimation, ie the first factor appearing in an unbalanced-panel equation with (say) three factors has to come from the three-factor EM estimation. So doing, it is possible to exploit the natural ranking of factors, since sequentially each one explains less variance of the original dataset. No such natural ranking of indicators is present with observed variables; therefore the other indicators are used in isolation in their own forecasting equation.

As regards multiple-factor regressions, it has become customary to either fix the number of parameters or select them following some information criteria such as the BIC. This option was not followed in this paper because of potential small-sample problems, and the known tendency of some information criteria tests to overstate the number of variables to pick up. Instead, a thorough testing of different combinations of factors was preferred. Hence, out-of-sample forecasts were first run with the first factor, then with the first and second factors, and finally with the first three factors. As already mentioned, the numerical problems found in the derivation of the fourth factor in the unbalanced panel with nominal variables (the fifth one, in the case of the complete database) justified taking into consideration only the first three factors. All factors entered with two lags, although different numbers of lags were tested.

12 M1 and M2 were also tested, as were real M1, M2 and M3. Nominal M3 was clearly the preferred choice.

Another key choice to make is the number of lags of the dependent variable entering the forecasting equation (ie, Δy_t). There, it is also the standard practice to either fix them a priori or choose them based on an information criteria test. We have in this case slightly departed from these choices and, after a large number of tests, decided to take as many lags as periods ahead to forecast. Thus, our number of lags is *h* and is made dependent on the particular forecasting horizon. This approach was taken after an exploration of alternative settings, and probably is a reflection of the relatively high persistence of inflation, as this imparts a lot of inertia to the dependent variable that may not be well captured unless a horizon-dependent number of lags of Δy_t are added. (It is important to note that the chosen equations are not recursive and are thus probably less prone to over-parameterisation problems.)

Results are presented in the form of the relative RMSE (root mean square error) of each equation against a convenient benchmark, for different forecasting horizons. The chosen benchmark is a simple version of (4.1) in which no indicator is used. Alternative specifications include as indicators the unemployment rate, GDP growth, the output gap and growth of M3. Dynamic factors comprise from one to three factors of the balanced and unbalanced panels. Each time, forecasting equations are estimated for a conveniently chosen subsample, out-of-sample forecasts made for the necessary steps ahead or until the end of the full sample has been reached, and corresponding RMSEs collected. The same operation is repeated for longer subsamples (extended recursively), each time collecting RMSEs. Finally, all RMSEs are averaged separately for each specific horizon. The RMSE for each combination of equation and horizon is divided by the corresponding one for the benchmark, and the resulting ratio shown in the table. A ratio of less than one means that, for that horizon, the corresponding equation can beat the benchmark, the opposite being true otherwise.

This procedure provides estimates of the true underlying forecasting performance of the equation by simple averaging of forecast errors. These forecasts take place within sample, but in periods not used to estimate the equation. At each step it is necessary to split the observed sample between a part dedicated to the estimation and a part dedicated to the calculation of forecast errors. If care is not exercised, too early a split date may lead to inaccuracies in the first estimations, and may bias the resulting RMSE test. Even worse, structural breaks in the data may lead to seemingly large RMSE numbers because of shifts in the forecasts made before any structural break. These problems dictate prudence in setting the initial date at which recursions are started, compounded in our case by the potentially unstable nature of euro area data. Accordingly, a relatively late first date for the out-of-sample exercises was chosen, ie 1995 Q1. Results for earlier starting dates were performed and are reported, although a structural break before 1995 cannot, in our view, be dismissed, so that greater weight should be attached to the findings for 1995 Q1.

Results from the forecasts are collected in Tables 1, 2 and 3. The first table is our base-case one: it shows results for out-of-sample exercises starting as of 1995 Q1; Table 2 has the same structure but with the initial date set at 1992 Q1; finally, Table 3 has an initial date of 1985 Q1, beyond which results would become highly unreliable. Each table is in turn divided between forecasts for HICP, for the consumption deflator (labelled PCD) and for the GDP deflator (labelled YED). Forecasting accuracy is always measured against a simple forecasting equation with no indicators, ie just lags of Δy, labelled in the table as AR. The comparison between the benchmark and each of the alternative equations is done as the ratio of the RMSEs of both. (Hence the row of ones at the top of each table, in the line corresponding to the benchmark itself.) As in Table 1, a value of less than one in a specific cell means that the corresponding equation has on average been more accurate than the benchmark. The comparisons are made for forecasts one to four periods ahead, and to eight periods ahead. The sample used and the date at which out-of-sample tests were started are also included on the right-hand side of the table.

A number of general conclusions can be drawn from the tables.

Factors generally have relatively good forecasting performance, particularly at medium-term horizons (beyond two quarters). Although factors never fare badly compared to alternative indicators at the one-quarter-ahead range, they have relative RMSEs that are generally lower in four- and eight-quarters-ahead forecasts. Regarding particular measures of inflation, nominal factors are preferable for HICP forecasts irrespective of the break date considered. In particular, forecasting regressions using two or three nominal factors coming from the unbalanced-panel estimates always match the best alternative indicator. To a lesser extent, the same applies for the consumption deflator (PCD in the table), although in this case a general degradation of forecasts can be perceived throughout the tables. On the other hand, the GDP deflator (YED in the table) is best forecast by non-nominal factors, this time by a rather considerable margin. Again, this is particularly true for medium-range forecasts using regressions with two or three unbalanced-panel factors.

Setting the starting date at 1992 Q1 leads to a visible worsening of forecasts. This is an outstanding feature in the tables: for all indicators, including factors, setting the recursion starting date at 1992 Q1 leads to visibly higher RMSEs than in either Table 1 or Table 3. Again, only the factors mentioned in the last paragraph are able to withstand the change in starting date without a large deterioration in results. An intriguing feature of the starting date comparison, upon which it would be unwise to draw unwarranted conclusions, is the relative similarity between Tables 1 and 3 (respectively, with dates at 1995 Q1 and 1985 Q1) and Table 2. This somewhat surprising feature certainly deserves further investigation since it may suggest that the period between 1992 and 1995 played a particular role in terms of structural changes affecting the underlying forecasting model.

Among alternative indicators (ie those not based on factors), unemployment outperforms the rest. The unemployment rate is very often the alternative indicator delivering lower RMSEs for most horizons, irrespective of the chosen inflation measure or recursion starting date. On the other hand, M3 is surprisingly good at forecasting HICP for all recursion starting dates (see Nicoletti-Altimari [2001] for similar findings.) This feature, however, is not found to hold for the consumption deflator and the GDP deflator, for which M3 has a reasonable but lacklustre performance. Finally, the output gap shows an unpromising forecasting performance, a fact in contrast with its widespread use in the literature but which could originate in the recursive end-of-sample revisions of the series performed. The Hodrick-Prescott filter was run each time an out-of-sample iteration was started, and this led to large revisions of the end point of the resulting output gap series. This conclusion, if granted, would highlight further the well known problem incurred in using filtered versions of potential output and the ensuing end-of-sample problem.

Additional tests were carried out that are not reported to save space. For instance, adding seasonal dummies and a German reunification dummy marginally improved the forecasting ability of the observed indicators but left almost unchanged that of the dynamic factors. Also, changing the number of lags for all indicators (tests were made for zero lags to four lags), although changing results, did not alter the conclusions reached.

6. Conclusions

Past developments in data collection and treatment have led over recent years to an explosion in the amount of data available for economic analysis. This increasing wealth of data calls for the exploitation of non-standard econometric techniques. This is specially the case for the euro area, for which specifically area-wide data are still a relative oddity but where a great wealth of data is available for the member countries. One technique developed recently by Stock and Watson (1999) is pursued in a companion paper for the analysis of trends in euro area-wide inflation (see Angelini et al [2001]), and is further used in this paper with the particular aim of forecasting area-wide inflation. The technique entails summarising a large amount of data as a small number of factors using a form of principal-component analysis, and using the resulting factors to forecast inflation. Technical aspects of the task are described, including data treatment and the setup used to forecast. Factors are extracted from a broad dataset comprising country data of the 11 member countries,[13] but also from a breakdown of the aforementioned dataset between price variables and non-price variables. Variables employed to measure inflation are HICP, the consumption deflator and the GDP deflator, for which simulated out-of-sample forecasts are run, using the extracted factors and a set of alternative indicators.

The first task reported in the paper is an in-sample analysis of the basic properties of the factors, and their links with the series included in the dataset which they summarise, which is an extension of evidence presented in our companion paper. One outstanding feature discovered is the (apparently) fundamental simplicity of nominal phenomena: price variables are mainly driven by a single factor mostly unrelated to other factors, while non-price developments show much more complex patterns. This feature is apparent through the double coincidence of two facts, namely a very strong first factor

[13] The analysis is readily extendable to the current 12 countries.

for the price-only dataset almost coincident with the first factor of the all-encompassing dataset, and lack of strong factors for the rest of the variables. Factors in this case are termed strong in terms of both their in-sample significance in the principal-component problem and their links to specific variables. This would point to a predominantly simple nominal behaviour in the dataset, compared to a much more complex behaviour for the rest of the variables. Furthermore, factors seem to be more strongly related to variables as a whole, ie the same type of series irrespective of the country, and have therefore relatively minor country-specific content.

On the other hand, the out-of-sample forecasting evidence found is fairly complex to describe. On top of that, the self-evident conclusion drawn from the in-sample analysis that nominal factors are the most relevant for inflation is now partially reversed. The main conclusion is that factors - but not only those reflecting nominal developments - may be good leading indicators of the various measures of inflation considered, particularly at medium-term horizons (four or eight quarters ahead). More precisely, HICP inflation is best forecast using many nominal factors (but not just the first one), while the GDP deflator inflation is best predicted using non-nominal factors. The consumption deflator is the more difficult to forecast, but shows a pattern similar in general terms to that of HICP. Alternative indicators broadly appear to have slightly worse forecasting properties, although the unemployment rate shows promising results while M3 also leads inflation in many of the cases analysed. Last but not least, experiments carried out changing the date at which the simulated out-of-sample forecasts start show that results are becoming worse for a specific date, 1992 Q1. This could be interpreted as a signal of an important structural break around this date, although evidence presented is certainly not sufficient to allow firm conclusions to be drawn on the issue.

Although the exercises performed in the context of this paper have been kept deliberately simple, they are promising enough to warrant further research, with a view to assessing in greater depth the specific contribution and relevance of the factor method. In terms of the in-sample analysis, for instance, performing rotations of factors in order to clarify their relationship with the original variables might further clarify the role of nominal phenomena. Regarding the out-of-sample analysis, two immediate developments of this work might be, first, to exploit the leading-indicator information of the factors as if in real life, ie checking the importance of updates and successive releases of data, and, second, to seek new ways of implementing the factor-based forecast. An example of the latter might be to extract factors from datasets also including the aggregated area-wide data, thereby drawing forecasts from the extrapolated series for the euro area resulting from the principal-component analysis using jointly all of the country and area-wide information.

Table 1

HICP

Model with 2 lags

Model	Periods Ahead					Date Range Covered		
	1	2	3	4	8	Start	End	Break
Benchmark								
AR	1.00	1.00	1.00	1.00	1.00	1980Q1	1999Q2	1995Q1
Unemployment	0.82	0.78	0.94	0.87	0.58	1980Q1	1999Q2	1995Q1
GDP	1.00	1.00	0.98	0.92	0.79	1980Q1	1999Q2	1995Q1
Output Gap	0.92	0.90	0.76	0.69	0.83	1980Q1	1999Q2	1995Q1
M3	0.69	0.65	1.02	0.90	0.87	1982Q3	1999Q2	1995Q1
Overall Factors, Balanced Panel								
F1B	0.88	0.89	1.09	1.05	0.92	1980Q1	1999Q2	1995Q1
F1B to F2B	0.89	0.86	1.06	1.06	0.92	1980Q1	1999Q2	1995Q1
F1B to F3B	0.84	0.87	1.13	1.06	1.11	1980Q1	1999Q2	1995Q1
Overall Factors, Unbalanced Panel								
F1U	0.86	0.90	1.25	1.24	1.09	1980Q1	1999Q2	1995Q1
F1U to F2U	0.85	0.72	0.99	0.99	0.94	1980Q1	1999Q2	1995Q1
F1U to F3U	0.84	0.69	0.85	0.74	0.75	1980Q1	1999Q2	1995Q1
Nominal Factors, Balanced Panel								
F1B	0.95	0.90	1.00	0.99	0.93	1980Q1	1999Q2	1995Q1
F1B to F2B	0.85	0.71	0.90	0.79	0.49	1980Q1	1999Q2	1995Q1
F1B to F3B	0.85	0.66	0.96	0.83	0.46	1980Q1	1999Q2	1995Q1
Nominal Factors, Unbalanced Panel								
F1U	0.98	0.94	1.08	1.03	0.96	1980Q1	1999Q2	1995Q1
F1U to F2U	0.90	0.66	0.80	0.73	0.49	1980Q1	1999Q2	1995Q1
F1U to F3U	0.91	0.59	0.82	0.76	0.53	1980Q1	1999Q2	1995Q1
Non-Nominal Factors, Balanced Panel								
F1B	1.00	1.04	1.11	1.06	0.87	1980Q1	1999Q2	1995Q1
F1B to F2B	0.90	0.89	1.04	0.98	0.84	1980Q1	1999Q2	1995Q1
F1B to F3B	0.82	0.87	1.13	1.03	1.14	1980Q1	1999Q2	1995Q1
Non-Nominal Factors, Unbalanced Panel								
F1U	1.01	1.05	1.20	1.21	1.01	1980Q1	1999Q2	1995Q1
F1U to F2U	0.82	0.75	0.91	0.83	0.63	1980Q1	1999Q2	1995Q1
F1U to F3U	0.80	0.77	1.00	0.73	0.48	1980Q1	1999Q2	1995Q1

PCD

Model with 2 lags

Model	Periods Ahead					Date Range Covered		
	1	2	3	4	8	Start	End	Break
Benchmark								
AR	1.00	1.00	1.00	1.00	1.00	1980Q1	1999Q2	1995Q1
Unemployment	0.79	0.78	0.81	0.86	0.48	1980Q1	1999Q2	1995Q1
GDP	1.92	1.98	1.08	1.04	0.85	1980Q1	1999Q2	1995Q1
Output Gap	1.75	1.78	0.83	0.78	0.89	1980Q1	1999Q2	1995Q1
M3	1.02	1.07	1.30	1.27	1.07	1982Q3	1999Q2	1995Q1
Overall Factors, Balanced Panel								
F1B	1.03	1.05	1.00	0.97	0.75	1980Q1	1999Q2	1995Q1
F1B to F2B	1.19	1.24	1.21	1.18	0.79	1980Q1	1999Q2	1995Q1
F1B to F3B	1.24	1.33	1.35	1.24	1.01	1980Q1	1999Q2	1995Q1
Overall Factors, Unbalanced Panel								
F1U	0.98	1.05	1.10	1.11	0.98	1980Q1	1999Q2	1995Q1
F1U to F2U	1.05	1.15	1.20	1.19	0.89	1980Q1	1999Q2	1995Q1
F1U to F3U	0.94	1.07	0.96	0.88	0.75	1980Q1	1999Q2	1995Q1
Nominal Factors, Balanced Panel								
F1B	1.17	1.11	1.10	1.12	0.83	1980Q1	1999Q2	1995Q1
F1B to F2B	1.01	1.03	1.02	1.02	0.48	1980Q1	1999Q2	1995Q1
F1B to F3B	0.99	1.03	1.08	1.15	0.52	1980Q1	1999Q2	1995Q1
Nominal Factors, Unbalanced Panel								
F1U	1.17	1.13	1.16	1.18	0.89	1980Q1	1999Q2	1995Q1
F1U to F2U	1.05	1.05	1.03	1.05	0.56	1980Q1	1999Q2	1995Q1
F1U to F3U	1.09	1.07	1.10	1.15	0.70	1980Q1	1999Q2	1995Q1
Non-Nominal Factors, Balanced Panel								
F1B	1.03	1.06	1.06	1.04	0.83	1980Q1	1999Q2	1995Q1
F1B to F2B	1.04	1.08	1.10	1.03	0.86	1980Q1	1999Q2	1995Q1
F1B to F3B	1.03	1.13	1.32	1.17	1.21	1980Q1	1999Q2	1995Q1
Non-Nominal Factors, Unbalanced Panel								
F1U	1.01	1.06	1.11	1.14	0.94	1980Q1	1999Q2	1995Q1
F1U to F2U	0.90	0.81	0.74	0.79	0.79	1980Q1	1999Q2	1995Q1
F1U to F3U	0.85	0.71	0.73	0.57	0.57	1980Q1	1999Q2	1995Q1

YED

Model with 2 lags

Model	Periods Ahead					Date Range Covered		
	1	2	3	4	8	Start	End	Break
Benchmark								
AR	1.00	1.00	1.00	1.00	1.00	1980Q1	1999Q2	1995Q1
Unemployment	0.97	0.90	0.75	0.75	0.26	1980Q1	1999Q2	1995Q1
GDP	2.09	2.30	0.97	0.98	1.23	1980Q1	1999Q2	1995Q1
Output Gap	1.91	2.07	0.75	0.74	1.29	1980Q1	1999Q2	1995Q1
M3	1.13	1.29	1.31	1.30	1.23	1982Q3	1999Q2	1995Q1
Overall Factors, Balanced Panel								
F1B	1.08	1.15	1.25	1.23	1.13	1980Q1	1999Q2	1995Q1
F1B to F2B	1.12	1.23	1.37	1.27	0.90	1980Q1	1999Q2	1995Q1
F1B to F3B	1.33	1.43	1.66	1.55	0.72	1980Q1	1999Q2	1995Q1
Overall Factors, Unbalanced Panel								
F1U	1.06	1.15	1.23	1.27	1.21	1980Q1	1999Q2	1995Q1
F1U to F2U	1.04	1.17	1.32	1.26	1.08	1980Q1	1999Q2	1995Q1
F1U to F3U	1.00	1.10	1.23	1.15	0.69	1980Q1	1999Q2	1995Q1
Nominal Factors, Balanced Panel								
F1B	1.13	1.24	1.38	1.35	1.35	1980Q1	1999Q2	1995Q1
F1B to F2B	1.06	1.21	1.36	1.34	1.38	1980Q1	1999Q2	1995Q1
F1B to F3B	1.01	1.20	1.41	1.43	1.64	1980Q1	1999Q2	1995Q1
Nominal Factors, Unbalanced Panel								
F1U	1.10	1.25	1.39	1.37	1.38	1980Q1	1999Q2	1995Q1
F1U to F2U	1.03	1.22	1.43	1.38	1.38	1980Q1	1999Q2	1995Q1
F1U to F3U	1.02	1.29	1.56	1.50	1.62	1980Q1	1999Q2	1995Q1
Non-Nominal Factors, Balanced Panel								
F1B	1.01	1.01	0.98	0.96	0.73	1980Q1	1999Q2	1995Q1
F1B to F2B	0.97	0.99	1.05	0.95	0.78	1980Q1	1999Q2	1995Q1
F1B to F3B	1.20	1.31	1.43	1.37	0.85	1980Q1	1999Q2	1995Q1
Non-Nominal Factors, Unbalanced Panel								
F1U	1.00	0.99	0.97	0.98	0.97	1980Q1	1999Q2	1995Q1
F1U to F2U	0.95	0.85	0.85	0.68	0.76	1980Q1	1999Q2	1995Q1
F1U to F3U	0.95	0.84	0.89	0.72	0.66	1980Q1	1999Q2	1995Q1

Table 2

HICP

Model with 2 lags

Model	Periods Ahead					Date Range Covered		
	1	2	3	4	8	Start	End	Break
Benchmark								
AR	1.00	1.00	1.00	1.00	1.00	1980Q1	1999Q2	1992Q1
Unemployment	0.94	0.99	1.31	1.30	1.06	1980Q1	1999Q2	1992Q1
GDP	1.01	1.02	1.06	0.98	0.92	1980Q1	1999Q2	1992Q1
Output Gap	0.94	0.98	1.40	1.71	2.69	1980Q1	1999Q2	1992Q1
M3	0.67	0.67	0.82	0.75	0.78	1982Q3	1999Q2	1992Q1
Overall Factors, Balanced Panel								
F1B	0.99	0.99	0.96	0.94	0.79	1980Q1	1999Q2	1992Q1
F1B to F2B	0.89	0.81	1.01	1.16	2.01	1980Q1	1999Q2	1992Q1
F1B to F3B	0.81	0.80	1.03	1.36	2.79	1980Q1	1999Q2	1992Q1
Overall Factors, Unbalanced Panel								
F1U	0.95	0.97	1.04	1.07	0.93	1980Q1	1999Q2	1992Q1
F1U to F2U	0.83	0.66	0.93	1.10	1.83	1980Q1	1999Q2	1992Q1
F1U to F3U	0.86	0.70	0.79	1.00	1.93	1980Q1	1999Q2	1992Q1
Nominal Factors, Balanced Panel								
F1B	0.88	0.83	0.86	0.88	0.90	1980Q1	1999Q2	1992Q1
F1B to F2B	0.79	0.66	0.79	0.74	0.89	1980Q1	1999Q2	1992Q1
F1B to F3B	0.80	0.65	0.86	0.78	0.89	1980Q1	1999Q2	1992Q1
Nominal Factors, Unbalanced Panel								
F1U	0.91	0.86	0.90	0.89	0.93	1980Q1	1999Q2	1992Q1
F1U to F2U	0.82	0.58	0.66	0.69	0.74	1980Q1	1999Q2	1992Q1
F1U to F3U	0.83	0.55	0.70	0.71	0.79	1980Q1	1999Q2	1992Q1
Non-Nominal Factors, Balanced Panel								
F1B	1.01	1.01	1.31	1.36	2.00	1980Q1	1999Q2	1992Q1
F1B to F2B	0.98	0.99	1.34	1.30	2.05	1980Q1	1999Q2	1992Q1
F1B to F3B	0.87	0.95	1.36	1.42	2.57	1980Q1	1999Q2	1992Q1
Non-Nominal Factors, Unbalanced Panel								
F1U	1.01	1.00	1.27	1.32	1.76	1980Q1	1999Q2	1992Q1
F1U to F2U	0.95	1.01	1.51	1.53	2.71	1980Q1	1999Q2	1992Q1
F1U to F3U	0.91	0.95	1.37	1.35	2.71	1980Q1	1999Q2	1992Q1

PCD

Model with 2 lags

Model	Periods Ahead					Date Range Covered		
	1	2	3	4	8	Start	End	Break
Benchmark								
AR	1.00	1.00	1.00	1.00	1.00	1980Q1	1999Q2	1992Q1
Unemployment	0.96	1.01	1.17	1.34	0.98	1980Q1	1999Q2	1992Q1
GDP	1.68	1.82	1.27	1.18	1.00	1980Q1	1999Q2	1992Q1
Output Gap	1.56	1.75	1.67	2.06	2.91	1980Q1	1999Q2	1992Q1
M3	0.97	0.99	1.09	1.04	0.96	1982Q3	1999Q2	1992Q1
Overall Factors, Balanced Panel								
F1B	1.08	1.06	0.96	0.97	0.74	1980Q1	1999Q2	1992Q1
F1B to F2B	1.06	1.05	1.12	1.53	1.85	1980Q1	1999Q2	1992Q1
F1B to F3B	0.96	1.08	1.26	1.74	2.52	1980Q1	1999Q2	1992Q1
Overall Factors, Unbalanced Panel								
F1U	1.03	1.05	1.00	0.98	0.87	1980Q1	1999Q2	1992Q1
F1U to F2U	0.95	0.98	1.12	1.46	1.53	1980Q1	1999Q2	1992Q1
F1U to F3U	0.94	0.94	0.91	1.25	1.57	1980Q1	1999Q2	1992Q1
Nominal Factors, Balanced Panel								
F1B	1.03	1.04	1.05	1.05	0.96	1980Q1	1999Q2	1992Q1
F1B to F2B	0.93	0.99	1.00	0.96	0.86	1980Q1	1999Q2	1992Q1
F1B to F3B	0.93	1.00	1.05	1.05	0.90	1980Q1	1999Q2	1992Q1
Nominal Factors, Unbalanced Panel								
F1U	1.02	1.04	1.07	1.07	1.00	1980Q1	1999Q2	1992Q1
F1U to F2U	0.90	0.92	0.95	1.03	0.98	1980Q1	1999Q2	1992Q1
F1U to F3U	0.96	0.95	0.96	1.02	1.03	1980Q1	1999Q2	1992Q1
Non-Nominal Factors, Balanced Panel								
F1B	1.05	1.01	1.14	1.59	1.71	1980Q1	1999Q2	1992Q1
F1B to F2B	0.96	1.00	1.18	1.56	1.72	1980Q1	1999Q2	1992Q1
F1B to F3B	0.86	0.98	1.26	1.67	2.19	1980Q1	1999Q2	1992Q1
Non-Nominal Factors, Unbalanced Panel								
F1U	1.05	0.99	1.19	1.55	1.53	1980Q1	1999Q2	1992Q1
F1U to F2U	0.97	1.04	1.26	1.71	2.11	1980Q1	1999Q2	1992Q1
F1U to F3U	0.93	0.92	1.12	1.46	1.95	1980Q1	1999Q2	1992Q1

YED

Model with 2 lags

Model	Periods Ahead					Date Range Covered		
	1	2	3	4	8	Start	End	Break
Benchmark								
AR	1.00	1.00	1.00	1.00	1.00	1980Q1	1999Q2	1992Q1
Unemployment	1.11	1.19	1.28	1.22	1.22	1980Q1	1999Q2	1992Q1
GDP	1.95	2.04	1.19	1.03	1.23	1980Q1	1999Q2	1992Q1
Output Gap	1.82	1.96	1.56	1.80	3.58	1980Q1	1999Q2	1992Q1
M3	1.10	1.14	1.19	1.14	1.11	1982Q3	1999Q2	1992Q1
Overall Factors, Balanced Panel								
F1B	1.34	1.49	1.84	1.64	1.34	1980Q1	1999Q2	1992Q1
F1B to F2B	1.19	1.22	1.40	1.08	2.10	1980Q1	1999Q2	1992Q1
F1B to F3B	1.17	1.23	1.42	1.18	2.05	1980Q1	1999Q2	1992Q1
Overall Factors, Unbalanced Panel								
F1U	1.27	1.44	1.78	1.66	1.40	1980Q1	1999Q2	1992Q1
F1U to F2U	1.12	1.14	1.30	1.03	1.95	1980Q1	1999Q2	1992Q1
F1U to F3U	1.16	1.17	1.27	1.03	1.71	1980Q1	1999Q2	1992Q1
Nominal Factors, Balanced Panel								
F1B	1.11	1.19	1.36	1.31	1.30	1980Q1	1999Q2	1992Q1
F1B to F2B	1.03	1.21	1.33	1.37	1.45	1980Q1	1999Q2	1992Q1
F1B to F3B	1.09	1.24	1.37	1.36	1.32	1980Q1	1999Q2	1992Q1
Nominal Factors, Unbalanced Panel								
F1U	1.11	1.19	1.36	1.31	1.32	1980Q1	1999Q2	1992Q1
F1U to F2U	1.02	1.17	1.34	1.30	1.30	1980Q1	1999Q2	1992Q1
F1U to F3U	1.05	1.24	1.43	1.41	1.52	1980Q1	1999Q2	1992Q1
Non-Nominal Factors, Balanced Panel								
F1B	1.08	0.99	0.89	1.04	2.52	1980Q1	1999Q2	1992Q1
F1B to F2B	1.20	1.21	1.31	1.12	2.08	1980Q1	1999Q2	1992Q1
F1B to F3B	1.19	1.20	1.36	1.29	2.13	1980Q1	1999Q2	1992Q1
Non-Nominal Factors, Unbalanced Panel								
F1U	1.09	1.01	0.93	1.02	2.29	1980Q1	1999Q2	1992Q1
F1U to F2U	0.98	0.88	0.86	0.95	2.34	1980Q1	1999Q2	1992Q1
F1U to F3U	0.98	0.83	0.80	0.86	1.99	1980Q1	1999Q2	1992Q1

Table 3

HICP

Model with 2 lags

Model	Periods Ahead					Date Range Covered		
	1	2	3	4	8	Start	End	Break
Benchmark								
AR	1.00	1.00	1.00	1.00	1.00	1980Q1	1999Q2	1985Q1
Unemployment	0.98	1.14	1.13	1.01	0.55	1980Q1	1999Q2	1985Q1
GDP	1.04	1.02	1.03	1.01	0.98	1980Q1	1999Q2	1985Q1
Output Gap	1.13	1.37	1.52	1.52	1.04	1980Q1	1999Q2	1985Q1
M3	0.77	0.80	0.94	0.89	0.82	1982Q3	1999Q2	1985Q1
Overall Factors, Balanced Panel								
F1B	0.94	0.95	0.92	0.98	0.91	1980Q1	1999Q2	1985Q1
F1B to F2B	0.82	0.73	0.90	1.10	1.28	1980Q1	1999Q2	1985Q1
F1B to F3B	0.79	0.73	0.91	1.16	1.29	1980Q1	1999Q2	1985Q1
Overall Factors, Unbalanced Panel								
F1U	0.92	0.96	0.94	0.99	0.92	1980Q1	1999Q2	1985Q1
F1U to F2U	0.79	0.68	0.85	1.02	1.28	1980Q1	1999Q2	1985Q1
F1U to F3U	0.82	0.68	0.78	1.01	1.15	1980Q1	1999Q2	1985Q1
Nominal Factors, Balanced Panel								
F1B	0.88	0.88	0.94	1.00	1.18	1980Q1	1999Q2	1985Q1
F1B to F2B	0.78	0.70	0.94	0.95	0.86	1980Q1	1999Q2	1985Q1
F1B to F3B	0.79	0.69	0.95	0.92	0.88	1980Q1	1999Q2	1985Q1
Nominal Factors, Unbalanced Panel								
F1U	0.90	0.92	0.97	1.02	1.02	1980Q1	1999Q2	1985Q1
F1U to F2U	0.78	0.65	0.76	0.72	0.66	1980Q1	1999Q2	1985Q1
F1U to F3U	0.78	0.58	0.69	0.69	0.71	1980Q1	1999Q2	1985Q1
Non-Nominal Factors, Balanced Panel								
F1B	1.02	1.06	1.12	1.23	1.28	1980Q1	1999Q2	1985Q1
F1B to F2B	0.94	0.97	1.07	1.18	1.33	1980Q1	1999Q2	1985Q1
F1B to F3B	0.91	1.03	1.13	1.27	1.41	1980Q1	1999Q2	1985Q1
Non-Nominal Factors, Unbalanced Panel								
F1U	1.02	1.06	1.14	1.24	1.29	1980Q1	1999Q2	1985Q1
F1U to F2U	0.93	1.02	1.14	1.23	1.35	1980Q1	1999Q2	1985Q1
F1U to F3U	0.93	1.00	1.09	1.21	1.38	1980Q1	1999Q2	1985Q1

PCD

Model with 2 lags

Model	Periods Ahead					Date Range Covered		
	1	2	3	4	8	Start	End	Break
Benchmark								
AR	1.00	1.00	1.00	1.00	1.00	1980Q1	1999Q2	1985Q1
Unemployment	1.04	1.04	1.06	0.98	0.54	1980Q1	1999Q2	1985Q1
GDP	1.56	1.44	1.10	1.05	1.04	1980Q1	1999Q2	1985Q1
Output Gap	1.69	1.93	1.62	1.58	1.11	1980Q1	1999Q2	1985Q1
M3	1.01	1.00	0.97	0.96	0.72	1982Q3	1999Q2	1985Q1
Overall Factors, Balanced Panel								
F1B	1.05	1.01	0.97	1.10	1.19	1980Q1	1999Q2	1985Q1
F1B to F2B	1.02	1.02	1.02	1.24	1.62	1980Q1	1999Q2	1985Q1
F1B to F3B	1.04	1.07	1.04	1.33	1.54	1980Q1	1999Q2	1985Q1
Overall Factors, Unbalanced Panel								
F1U	1.04	1.00	1.00	1.12	1.14	1980Q1	1999Q2	1985Q1
F1U to F2U	0.99	1.00	1.05	1.22	1.65	1980Q1	1999Q2	1985Q1
F1U to F3U	1.05	0.98	0.94	1.16	1.41	1980Q1	1999Q2	1985Q1
Nominal Factors, Balanced Panel								
F1B	1.05	1.03	0.98	1.04	1.16	1980Q1	1999Q2	1985Q1
F1B to F2B	0.94	0.99	0.96	1.04	0.99	1980Q1	1999Q2	1985Q1
F1B to F3B	0.94	0.96	1.02	1.08	0.81	1980Q1	1999Q2	1985Q1
Nominal Factors, Unbalanced Panel								
F1U	1.06	1.04	1.02	1.10	1.08	1980Q1	1999Q2	1985Q1
F1U to F2U	0.91	0.90	0.89	0.86	0.82	1980Q1	1999Q2	1985Q1
F1U to F3U	0.92	0.90	0.90	0.84	0.80	1980Q1	1999Q2	1985Q1
Non-Nominal Factors, Balanced Panel								
F1B	1.05	1.02	1.04	1.26	1.66	1980Q1	1999Q2	1985Q1
F1B to F2B	0.98	1.00	1.04	1.28	1.79	1980Q1	1999Q2	1985Q1
F1B to F3B	1.01	1.05	1.11	1.40	1.75	1980Q1	1999Q2	1985Q1
Non-Nominal Factors, Unbalanced Panel								
F1U	1.06	1.02	1.07	1.27	1.71	1980Q1	1999Q2	1985Q1
F1U to F2U	1.03	1.00	1.13	1.29	1.79	1980Q1	1999Q2	1985Q1
F1U to F3U	1.05	1.00	1.06	1.28	1.68	1980Q1	1999Q2	1985Q1

YED

Model with 2 lags

Model	Periods Ahead					Date Range Covered		
	1	2	3	4	8	Start	End	Break
Benchmark								
AR	1.00	1.00	1.00	1.00	1.00	1980Q1	1999Q2	1985Q1
Unemployment	1.03	1.16	1.24	1.03	0.54	1980Q1	1999Q2	1985Q1
GDP	1.55	1.64	1.23	1.11	1.38	1980Q1	1999Q2	1985Q1
Output Gap	1.68	2.21	1.80	1.66	1.47	1980Q1	1999Q2	1985Q1
M3	1.09	1.07	1.04	0.97	2.70	1982Q3	1999Q2	1985Q1
Overall Factors, Balanced Panel								
F1B	0.99	1.02	1.13	1.05	0.74	1980Q1	1999Q2	1985Q1
F1B to F2B	1.01	1.06	1.04	0.89	1.16	1980Q1	1999Q2	1985Q1
F1B to F3B	1.05	1.13	1.09	0.94	1.06	1980Q1	1999Q2	1985Q1
Overall Factors, Unbalanced Panel								
F1U	0.97	1.00	1.12	1.02	0.75	1980Q1	1999Q2	1985Q1
F1U to F2U	0.98	1.03	1.05	0.84	0.99	1980Q1	1999Q2	1985Q1
F1U to F3U	1.07	1.11	1.08	0.89	0.89	1980Q1	1999Q2	1985Q1
Nominal Factors, Balanced Panel								
F1B	1.00	1.01	1.01	1.02	0.67	1980Q1	1999Q2	1985Q1
F1B to F2B	0.98	1.04	1.01	1.09	0.79	1980Q1	1999Q2	1985Q1
F1B to F3B	1.00	1.07	1.08	1.12	0.74	1980Q1	1999Q2	1985Q1
Nominal Factors, Unbalanced Panel								
F1U	0.98	1.02	1.06	1.03	0.63	1980Q1	1999Q2	1985Q1
F1U to F2U	0.96	1.04	0.99	1.03	0.69	1980Q1	1999Q2	1985Q1
F1U to F3U	1.00	1.11	1.13	1.16	0.65	1980Q1	1999Q2	1985Q1
Non-Nominal Factors, Balanced Panel								
F1B	1.03	1.03	1.04	0.97	1.11	1980Q1	1999Q2	1985Q1
F1B to F2B	1.00	1.04	1.04	0.88	1.06	1980Q1	1999Q2	1985Q1
F1B to F3B	1.01	1.05	1.06	0.92	0.89	1980Q1	1999Q2	1985Q1
Non-Nominal Factors, Unbalanced Panel								
F1U	1.03	1.05	1.07	1.00	0.98	1980Q1	1999Q2	1985Q1
F1U to F2U	0.91	0.91	0.94	0.81	0.96	1980Q1	1999Q2	1985Q1
F1U to F3U	0.93	0.90	0.88	0.82	0.78	1980Q1	1999Q2	1985Q1

Appendix A: Loadings

Table 1
Balanced panel

Variable	Loadings					Loadings Squared				
	F1	F2	F3	F4	F5	F1	F2	F3	F4	F5
CPIAT	0.73	-0.11	0.22	-0.09	-0.18	0.53	0.01	0.05	0.01	0.03
CPIBE	0.84	-0.03	-0.08	0.05	0.09	0.70	0.00	0.01	0.00	0.01
CPIDE	0.69	-0.06	0.44	-0.15	0.02	0.47	0.00	0.19	0.02	0.00
CPIES	0.82	-0.15	-0.25	0.20	-0.19	0.67	0.02	0.06	0.04	0.04
CPIFI	0.78	-0.31	-0.05	0.32	0.04	0.61	0.09	0.00	0.10	0.00
CPIFR	0.92	-0.20	-0.17	0.15	0.01	0.84	0.04	0.03	0.02	0.00
CPIIE	0.83	-0.20	-0.03	0.20	0.15	0.68	0.04	0.00	0.04	0.02
CPIIT	0.90	-0.20	-0.13	0.15	0.03	0.80	0.04	0.02	0.02	0.00
CPINL	0.75	-0.13	0.16	-0.12	-0.07	0.56	0.02	0.03	0.01	0.01
CPIPT	0.70	-0.12	-0.31	0.15	-0.23	0.48	0.01	0.10	0.02	0.06
MTDAT	0.45	-0.34	0.23	-0.29	0.12	0.20	0.12	0.05	0.08	0.01
MTDDE	0.54	-0.44	0.20	-0.40	0.19	0.29	0.19	0.04	0.16	0.04
MTDES	0.75	-0.15	0.11	-0.18	0.29	0.56	0.02	0.01	0.03	0.09
MTDFI	0.54	-0.18	0.24	-0.19	0.04	0.29	0.03	0.06	0.04	0.00
MTDFR	0.64	-0.39	-0.01	-0.29	0.24	0.41	0.15	0.00	0.09	0.06
MTDIT	0.64	-0.21	0.24	-0.36	0.25	0.41	0.05	0.06	0.13	0.06
PCDAT	0.74	-0.05	0.12	-0.10	-0.18	0.55	0.00	0.02	0.01	0.03
PCDDE	0.66	-0.11	0.42	-0.09	0.12	0.43	0.01	0.18	0.01	0.01
PCDES	0.80	-0.09	-0.22	0.27	-0.18	0.63	0.01	0.05	0.07	0.03
PCDFR	0.91	-0.18	-0.20	0.14	0.00	0.82	0.03	0.04	0.02	0.00
PCDIT	0.92	-0.18	-0.14	0.15	0.03	0.84	0.03	0.02	0.02	0.00
PCDFI	0.79	-0.16	0.01	0.26	-0.05	0.62	0.03	0.00	0.07	0.00
PPIAT	0.58	-0.40	0.18	-0.19	0.04	0.34	0.16	0.03	0.04	0.00
PPIDE	0.68	-0.51	0.15	-0.25	0.11	0.46	0.26	0.02	0.06	0.01
PPIES	0.85	-0.20	-0.24	-0.08	-0.01	0.72	0.04	0.06	0.01	0.00
PPIFI	0.76	-0.36	0.11	-0.16	0.17	0.58	0.13	0.01	0.03	0.03
PPIFR	0.72	-0.34	-0.32	-0.08	0.12	0.52	0.12	0.10	0.01	0.01
PPINL	0.64	-0.43	0.14	-0.34	0.05	0.40	0.18	0.02	0.12	0.00
XTDAT	0.62	-0.40	0.03	-0.32	0.01	0.39	0.16	0.00	0.10	0.00
XTDDE	0.71	-0.43	0.07	-0.26	0.12	0.51	0.18	0.00	0.07	0.01
XTDES	0.88	-0.05	-0.13	-0.05	0.15	0.78	0.00	0.02	0.00	0.02
XTDFI	0.54	-0.19	0.04	-0.19	-0.06	0.29	0.04	0.00	0.04	0.00
XTDFR	0.77	-0.24	-0.24	-0.16	0.23	0.59	0.06	0.06	0.03	0.06
XTDIT	0.73	-0.23	0.11	-0.12	0.16	0.54	0.05	0.01	0.01	0.02
YEDAT	0.55	0.03	-0.04	0.16	-0.33	0.30	0.00	0.00	0.02	0.11
YEDDE	0.44	0.02	0.23	0.31	-0.25	0.20	0.00	0.05	0.09	0.06
YEDES	0.71	-0.12	-0.32	0.29	-0.29	0.51	0.01	0.10	0.08	0.09
YEDFI	0.57	-0.19	-0.15	0.27	0.14	0.33	0.04	0.02	0.07	0.02
YEDFR	0.83	-0.07	-0.27	0.25	-0.03	0.70	0.01	0.07	0.06	0.00
YEDIT	0.88	-0.23	-0.16	0.21	-0.01	0.77	0.05	0.03	0.04	0.00
CAPDE	-0.50	-0.50	0.43	0.32	-0.24	0.25	0.25	0.18	0.10	0.06
CAPES	0.06	-0.62	-0.40	0.42	0.17	0.00	0.38	0.16	0.18	0.03
CAPFR	-0.28	-0.46	0.32	0.39	-0.25	0.08	0.21	0.10	0.15	0.06
CAPIT	-0.62	-0.45	0.39	0.11	0.01	0.38	0.20	0.15	0.01	0.00
CAPNL	-0.79	-0.35	0.33	0.06	-0.09	0.62	0.12	0.11	0.00	0.01
CAPPT	-0.39	-0.54	0.15	0.22	0.17	0.15	0.29	0.02	0.05	0.03
ERNAT	0.37	-0.08	0.21	0.31	-0.15	0.14	0.01	0.04	0.10	0.02
ERNDE	0.23	-0.07	0.25	0.17	-0.08	0.05	0.01	0.06	0.03	0.01
ERNES	0.54	-0.07	0.00	0.16	-0.04	0.29	0.00	0.00	0.03	0.00
ERNFI	0.31	-0.28	-0.12	0.12	0.06	0.10	0.08	0.01	0.02	0.00
ERNFR	0.85	-0.12	-0.22	0.27	-0.02	0.72	0.01	0.05	0.07	0.00
ERNIT	0.82	-0.13	-0.17	0.21	-0.03	0.68	0.02	0.03	0.04	0.00
ERNNL	0.34	0.04	0.00	0.08	-0.04	0.12	0.00	0.00	0.01	0.00

Table 1 (cont)

Balanced panel

Variable	Loadings					Loadings Squared				
	F1	F2	F3	F4	F5	F1	F2	F3	F4	F5
GDPAT	-0.09	-0.36	-0.22	-0.26	-0.27	0.01	0.13	0.05	0.07	0.07
GDPDE	-0.12	-0.30	-0.39	-0.20	-0.52	0.01	0.09	0.15	0.04	0.27
GDPES	-0.55	-0.36	-0.27	0.05	0.28	0.31	0.13	0.07	0.00	0.08
GDPFI	-0.02	-0.21	-0.44	-0.17	0.28	0.00	0.04	0.19	0.03	0.08
GDPFR	-0.17	-0.46	-0.49	-0.13	-0.12	0.03	0.22	0.24	0.02	0.01
GDPIT	0.03	-0.42	-0.33	-0.11	-0.17	0.00	0.18	0.11	0.01	0.03
GDPNL	-0.29	-0.19	-0.14	-0.14	-0.18	0.09	0.03	0.02	0.02	0.03
HSTBE	-0.22	-0.16	-0.12	-0.37	-0.10	0.05	0.03	0.01	0.14	0.01
HSTES	-0.14	0.02	-0.12	-0.11	0.11	0.02	0.00	0.02	0.01	0.01
HSTFI	-0.08	-0.38	-0.19	0.18	0.35	0.01	0.15	0.03	0.03	0.12
HSTFR	-0.20	0.02	-0.24	-0.17	0.06	0.04	0.00	0.06	0.03	0.00
HSTNL	0.04	-0.07	-0.11	-0.15	-0.07	0.00	0.00	0.01	0.02	0.00
LFNES	-0.27	0.04	-0.12	-0.12	0.16	0.07	0.00	0.01	0.01	0.02
LFNFI	0.12	-0.15	-0.11	-0.01	0.30	0.01	0.02	0.01	0.00	0.09
LFNFR	-0.07	-0.12	0.26	-0.08	-0.33	0.00	0.01	0.07	0.01	0.11
LFNIT	0.02	-0.22	-0.20	0.26	0.07	0.00	0.05	0.04	0.07	0.00
LFNNL	0.24	-0.22	0.24	0.16	0.26	0.06	0.05	0.06	0.02	0.07
LNNAT	-0.02	-0.09	0.09	-0.10	-0.29	0.00	0.01	0.01	0.01	0.08
LNNBE	-0.58	-0.43	-0.22	0.10	0.11	0.34	0.18	0.05	0.01	0.01
LNNDE	-0.10	-0.61	-0.07	0.36	-0.25	0.01	0.37	0.00	0.13	0.06
LNNES	-0.73	-0.30	-0.23	0.13	0.27	0.54	0.09	0.05	0.02	0.07
LNNFI	0.03	-0.51	-0.43	-0.11	0.47	0.00	0.26	0.18	0.01	0.22
LNNFR	-0.56	-0.49	-0.03	0.15	0.14	0.31	0.24	0.00	0.02	0.02
LNNIE	-0.50	-0.18	0.01	-0.01	0.13	0.25	0.03	0.00	0.00	0.02
LNNIT	-0.03	-0.31	-0.14	0.39	0.08	0.00	0.10	0.02	0.15	0.01
LNNPT	-0.24	-0.49	0.08	0.16	-0.10	0.06	0.24	0.01	0.03	0.01
LTIAT	0.16	-0.59	0.35	-0.07	-0.12	0.03	0.34	0.12	0.00	0.01
LTIBE	0.36	-0.59	0.29	-0.21	-0.02	0.13	0.34	0.08	0.04	0.00
LTIDE	0.22	-0.61	0.20	-0.15	-0.12	0.05	0.37	0.04	0.02	0.01
LTIFI	0.21	-0.50	0.10	0.04	0.06	0.05	0.25	0.01	0.00	0.00
LTIFR	0.29	-0.54	0.32	-0.17	0.04	0.09	0.29	0.11	0.03	0.00
LTIIE	0.25	-0.39	0.24	-0.20	-0.22	0.06	0.15	0.06	0.04	0.05
LTIIT	0.26	-0.47	0.32	-0.03	0.10	0.07	0.22	0.10	0.00	0.01
LTINL	0.14	-0.67	0.26	-0.20	-0.14	0.02	0.44	0.07	0.04	0.02
MFBBE	-0.61	-0.59	0.17	0.09	0.14	0.37	0.34	0.03	0.01	0.02
MFBDE	-0.38	-0.67	0.21	0.39	-0.20	0.14	0.44	0.04	0.15	0.04
MFBFR	-0.48	-0.72	-0.05	0.21	0.26	0.23	0.51	0.00	0.04	0.07
MFBIE	-0.61	-0.42	0.06	-0.16	-0.03	0.38	0.18	0.00	0.03	0.00
MFBIT	-0.59	-0.66	0.19	-0.04	0.11	0.34	0.44	0.04	0.00	0.01
MFBNL	-0.76	-0.44	0.22	-0.03	-0.02	0.58	0.20	0.05	0.00	0.00
MFSBE	0.29	0.37	-0.12	0.01	-0.18	0.08	0.14	0.01	0.00	0.03
MFSDE	0.40	0.66	-0.20	-0.26	0.25	0.16	0.44	0.04	0.07	0.06
MFSFR	0.47	0.55	0.07	-0.09	-0.31	0.22	0.31	0.00	0.01	0.10
MFSIE	0.27	0.50	0.10	0.00	0.09	0.07	0.25	0.01	0.00	0.01
MFSIT	0.46	0.56	-0.23	0.18	-0.25	0.21	0.31	0.05	0.03	0.06
MFSNL	0.77	0.29	-0.19	0.12	0.08	0.59	0.09	0.04	0.01	0.01

Table 1 (cont)

Balanced panel

Variable	Loadings					Loadings Squared				
	F1	F2	F3	F4	F5	F1	F2	F3	F4	F5
MTRAT	-0.10	-0.19	-0.16	-0.18	-0.19	0.01	0.04	0.03	0.03	0.04
MTRDE	-0.22	-0.38	-0.31	-0.20	-0.29	0.05	0.14	0.10	0.04	0.08
MTRES	-0.58	-0.36	-0.27	-0.01	0.04	0.33	0.13	0.07	0.00	0.00
MTRFI	-0.05	-0.12	-0.02	-0.18	0.24	0.00	0.01	0.00	0.03	0.06
MTRFR	-0.19	-0.45	-0.23	-0.20	-0.02	0.04	0.20	0.05	0.04	0.00
MTRIT	-0.12	-0.41	-0.27	-0.27	-0.32	0.01	0.17	0.07	0.07	0.10
MTRNL	-0.30	-0.22	-0.44	-0.35	-0.12	0.09	0.05	0.19	0.12	0.01
PCEAT	-0.01	-0.11	-0.15	-0.06	-0.21	0.00	0.01	0.02	0.00	0.04
PCEDE	-0.20	-0.15	-0.35	0.00	-0.51	0.04	0.02	0.13	0.00	0.26
PCEES	-0.65	-0.44	-0.15	0.19	0.09	0.42	0.19	0.02	0.04	0.01
PCEFI	-0.06	-0.15	-0.49	-0.12	0.38	0.00	0.02	0.24	0.01	0.14
PCEFR	-0.10	-0.23	-0.37	0.04	-0.23	0.01	0.05	0.14	0.00	0.05
PCEIT	0.01	-0.64	-0.26	0.08	-0.14	0.00	0.41	0.07	0.01	0.02
PCENL	-0.36	-0.05	-0.21	0.02	-0.27	0.13	0.00	0.04	0.00	0.07
PIHBE	-0.10	-0.01	-0.02	0.01	0.00	0.01	0.00	0.00	0.00	0.00
PIHFI	-0.01	-0.03	-0.04	-0.05	0.13	0.00	0.00	0.00	0.00	0.02
PIHFR	-0.09	-0.02	-0.14	-0.10	-0.09	0.01	0.00	0.02	0.01	0.01
PIHNL	-0.06	-0.07	-0.14	-0.21	-0.13	0.00	0.01	0.02	0.05	0.02
RSLAT	-0.02	-0.14	-0.13	-0.05	-0.14	0.00	0.02	0.02	0.00	0.02
RSLBE	-0.20	-0.23	-0.17	0.09	-0.10	0.04	0.05	0.03	0.01	0.01
RSLDE	-0.14	-0.19	-0.31	0.04	-0.39	0.02	0.03	0.10	0.00	0.15
RSLFR	-0.08	-0.12	-0.11	-0.01	-0.07	0.01	0.01	0.01	0.00	0.00
RSLIE	-0.26	-0.10	-0.06	-0.30	-0.09	0.07	0.01	0.00	0.09	0.01
RSLNL	-0.34	-0.04	-0.05	-0.02	0.02	0.12	0.00	0.00	0.00	0.00
STIAT	0.05	-0.69	0.35	0.05	-0.04	0.00	0.48	0.12	0.00	0.00
STIBE	0.22	-0.58	0.17	-0.03	-0.16	0.05	0.34	0.03	0.00	0.02
STIDE	0.12	-0.64	0.22	-0.13	-0.16	0.01	0.41	0.05	0.02	0.03
STIES	0.05	-0.09	-0.11	0.07	-0.08	0.00	0.01	0.01	0.00	0.01
STIFI	0.10	-0.51	0.12	0.22	0.12	0.01	0.26	0.01	0.05	0.01
STIFR	0.19	-0.45	0.23	-0.11	0.06	0.04	0.20	0.05	0.01	0.00
STIIE	0.11	-0.22	0.15	0.06	-0.05	0.01	0.05	0.02	0.00	0.00
STIIT	0.22	-0.45	0.21	-0.01	0.00	0.05	0.20	0.05	0.00	0.00
STINL	0.06	-0.43	-0.01	-0.13	-0.29	0.00	0.19	0.00	0.02	0.09
STIPT	0.33	-0.23	-0.14	0.14	-0.04	0.11	0.05	0.02	0.02	0.00
UNRAT	0.23	0.44	0.00	0.34	0.06	0.05	0.19	0.00	0.12	0.00
UNRBE	0.44	0.43	0.21	-0.09	-0.07	0.19	0.18	0.04	0.01	0.01
UNRDE	0.47	0.52	-0.04	-0.12	0.43	0.22	0.27	0.00	0.01	0.18
UNRES	0.74	0.37	0.21	-0.13	-0.27	0.55	0.13	0.05	0.02	0.07
UNRFR	0.48	0.40	0.14	-0.26	-0.32	0.23	0.16	0.02	0.07	0.11
UNRFI	0.09	0.52	0.41	0.11	-0.39	0.01	0.28	0.17	0.01	0.16
UNRIE	0.66	0.31	0.09	0.13	-0.18	0.43	0.10	0.01	0.02	0.03
UNRIT	0.19	0.31	-0.09	-0.24	-0.05	0.04	0.10	0.01	0.06	0.00
UNRNL	0.59	0.39	-0.11	-0.01	0.22	0.35	0.16	0.01	0.00	0.05
UNRPT	0.35	0.51	0.09	-0.31	-0.20	0.12	0.26	0.01	0.10	0.04
WINAT	0.05	-0.02	0.04	0.16	-0.09	0.00	0.00	0.00	0.03	0.01
WINDE	0.17	-0.32	0.05	0.10	-0.47	0.03	0.10	0.00	0.01	0.22
WINFR	0.76	-0.32	-0.26	0.30	-0.01	0.58	0.11	0.07	0.09	0.00
WINIT	0.74	-0.35	-0.14	0.18	0.02	0.55	0.12	0.02	0.03	0.00
XTRAT	-0.02	-0.18	-0.28	-0.30	-0.09	0.00	0.03	0.08	0.09	0.01
XTRDE	0.02	-0.40	-0.15	-0.38	-0.21	0.00	0.16	0.02	0.15	0.04
XTRES	0.00	0.23	-0.12	-0.52	-0.02	0.00	0.05	0.01	0.27	0.00
XTRFI	-0.01	0.01	-0.01	-0.33	0.04	0.00	0.00	0.00	0.11	0.00
XTRFR	-0.04	-0.33	-0.10	-0.53	0.04	0.00	0.11	0.01	0.29	0.00
XTRIT	0.03	-0.02	-0.09	-0.37	-0.17	0.00	0.00	0.01	0.13	0.03
XTRNL	-0.14	-0.17	-0.42	-0.42	-0.27	0.02	0.03	0.18	0.18	0.07

Table 2
Unbalanced Panel

Variable	Loadings			Loadings Squared		
	F1	F2	F3	F1	F2	F3
MTDIE	0.71	-0.25	-0.29	0.51	0.06	0.08
MTDNL	0.47	-0.33	-0.26	0.22	0.11	0.07
MTDBE	0.02	-0.27	-0.54	0.00	0.07	0.29
MTDPT	0.23	-0.30	-0.36	0.05	0.09	0.13
PCDIE	0.89	0.01	0.00	0.79	0.00	0.00
PCDBE	0.37	-0.13	-0.13	0.14	0.02	0.02
PCDPT	0.47	-0.32	0.45	0.22	0.10	0.20
PCDNL	0.57	-0.06	0.05	0.33	0.00	0.00
PPIBE	0.68	-0.29	-0.33	0.46	0.08	0.11
PPIPT	0.40	0.00	-0.18	0.16	0.00	0.03
PPIIT	0.87	-0.23	-0.16	0.75	0.05	0.03
PPIIE	0.26	-0.24	-0.23	0.07	0.06	0.05
ULCBE	0.40	0.25	0.44	0.16	0.06	0.19
ULCDE	0.25	0.01	0.39	0.06	0.00	0.15
ULCES	0.57	-0.08	0.27	0.32	0.01	0.07
ULCFI	-0.13	-0.32	0.19	0.02	0.10	0.04
ULCFR	0.18	0.07	0.51	0.03	0.00	0.26
ULCIT	0.78	-0.13	0.21	0.61	0.02	0.05
ULCNL	0.04	0.18	0.33	0.00	0.03	0.11
WPIDE	0.16	-0.18	-0.61	0.03	0.03	0.37
WPIFI	0.48	0.22	-0.19	0.23	0.05	0.04
WPIIT	0.16	-0.22	0.01	0.03	0.05	0.00
XTDNL	0.45	-0.33	-0.35	0.20	0.11	0.12
XTDIE	0.73	-0.01	-0.36	0.53	0.00	0.13
XTDBE	0.00	-0.26	-0.48	0.00	0.07	0.23
XTDPT	0.21	-0.31	-0.15	0.04	0.09	0.02
YEDIE	0.91	-0.18	0.05	0.82	0.03	0.00
YEDNL	0.39	-0.06	0.01	0.15	0.00	0.00
YEDBE	0.50	-0.09	0.12	0.25	0.01	0.01
YEDPT	0.39	-0.26	0.52	0.15	0.07	0.27
CAPIE	-0.78	-0.12	0.02	0.62	0.01	0.00
CRDBE	-0.08	-0.48	0.13	0.01	0.23	0.02
CRDDE	0.12	-0.18	0.27	0.02	0.03	0.07
CRDFR	0.16	-0.16	0.15	0.02	0.03	0.02
EEFAT	-0.03	-0.03	0.42	0.00	0.00	0.18
EEFBE	-0.04	-0.08	0.44	0.00	0.01	0.19
EEFDE	-0.06	-0.03	0.43	0.00	0.00	0.19
EEFES	-0.17	-0.53	0.20	0.03	0.28	0.04
EEFFI	-0.25	-0.45	-0.16	0.06	0.20	0.03
EEFFR	0.00	-0.03	0.41	0.00	0.00	0.17
EEFIE	-0.06	-0.11	0.37	0.00	0.01	0.14
EEFIT	-0.30	-0.18	0.15	0.09	0.03	0.02
EEFNL	-0.08	0.02	0.45	0.01	0.00	0.20
EEFPT	-0.28	-0.18	0.07	0.08	0.03	0.01
ERNBE	0.68	-0.13	0.21	0.46	0.02	0.05
ERNIE	0.68	-0.15	0.10	0.46	0.02	0.01
GDPBE	-0.15	-0.43	-0.27	0.02	0.19	0.07
GDPIE	-0.30	-0.21	-0.21	0.09	0.04	0.04
GDPPT	-0.18	-0.32	-0.13	0.03	0.10	0.02
HSTDE	0.10	0.12	-0.28	0.01	0.01	0.08
LFNAT	0.20	0.08	0.01	0.04	0.01	0.00
LFNBE	0.17	-0.02	-0.11	0.03	0.00	0.01
LFNDE	0.21	0.04	-0.21	0.05	0.00	0.05
LFNIE	-0.24	0.22	-0.03	0.06	0.05	0.00
LFNPT	-0.04	-0.17	0.00	0.00	0.03	0.00
LNIBE	-0.27	-0.33	0.26	0.07	0.11	0.07
LNIDE	0.32	-0.20	0.24	0.10	0.04	0.06
LNIIT	0.00	-0.38	0.53	0.00	0.14	0.28
LNNNL	-0.41	-0.45	0.28	0.17	0.20	0.08
LTIES	0.14	-0.36	0.01	0.02	0.13	0.00
LTIPT	-0.03	-0.34	-0.28	0.00	0.12	0.08

Table 2 (cont)

Unbalanced Panel

Variable	Loadings			Loadings Squared		
	F1	F2	F3	F1	F2	F3
M1AT	-0.41	0.20	-0.24	0.16	0.04	0.06
M1BE	-0.09	0.15	0.05	0.01	0.02	0.00
M1DE	-0.23	0.14	0.21	0.06	0.02	0.04
M1ES	-0.04	-0.48	0.22	0.00	0.23	0.05
M1FI	0.16	-0.03	-0.16	0.03	0.00	0.03
M1FR	0.23	-0.15	0.05	0.05	0.02	0.00
M1IE	-0.21	-0.06	-0.28	0.05	0.00	0.08
M1IT	0.23	-0.04	0.10	0.05	0.00	0.01
M1NL	-0.22	0.19	0.11	0.05	0.04	0.01
M1PT	0.05	0.01	0.26	0.00	0.00	0.07
M2AT	0.35	0.21	0.26	0.12	0.04	0.07
M2BE	-0.13	-0.01	0.01	0.02	0.00	0.00
M2DE	0.02	0.38	0.25	0.00	0.14	0.06
M2ES	0.59	-0.28	0.12	0.35	0.08	0.01
M2FI	0.41	-0.37	0.13	0.16	0.14	0.02
M2FR	0.40	-0.31	-0.11	0.16	0.10	0.01
M2IE	-0.02	0.11	-0.11	0.00	0.01	0.01
M2IT	0.53	0.09	0.22	0.28	0.01	0.05
M2NL	0.10	-0.07	0.36	0.01	0.00	0.13
M2PT	0.70	-0.01	0.27	0.48	0.00	0.07
M3AT	0.36	0.20	0.24	0.13	0.04	0.06
M3BE	-0.05	0.16	0.12	0.00	0.03	0.01
M3DE	0.22	0.30	0.12	0.05	0.09	0.02
M3ES	0.52	-0.33	0.14	0.27	0.11	0.02
M3FI	0.31	-0.24	0.13	0.10	0.06	0.02
M3FR	0.35	-0.50	0.25	0.12	0.25	0.06
M3IE	-0.08	0.08	-0.21	0.01	0.01	0.04
M3IT	0.52	0.04	0.24	0.27	0.00	0.06
M3NL	0.08	-0.10	0.36	0.01	0.01	0.13
M3PT	0.69	-0.05	0.25	0.47	0.00	0.06
MFBAT	-0.10	-0.78	0.37	0.01	0.61	0.14
MFBES	-0.70	-0.68	-0.09	0.49	0.46	0.01
MFBFI	-0.39	-0.61	-0.38	0.15	0.37	0.14
MFBPT	-0.57	-0.72	0.07	0.33	0.52	0.00
MFOBE	-0.33	-0.59	-0.14	0.11	0.35	0.02
MFODE	-0.38	-0.67	-0.06	0.15	0.44	0.00
MFOES	-0.43	-0.56	-0.08	0.18	0.32	0.01
MFOFI	-0.28	-0.11	-0.55	0.08	0.01	0.30
MFOFR	-0.41	-0.71	0.17	0.17	0.51	0.03
MFOIE	-0.65	-0.28	-0.19	0.42	0.08	0.04
MFOIT	-0.63	-0.59	-0.02	0.39	0.34	0.00
MFONL	-0.55	-0.38	-0.20	0.31	0.15	0.04
MFOPT	-0.50	-0.69	0.00	0.25	0.48	0.00
MFSAT	0.14	0.83	-0.21	0.02	0.69	0.04
MFSES	0.65	0.70	0.19	0.42	0.49	0.04
MFSPT	0.45	0.48	0.17	0.21	0.23	0.03
MTRBE	-0.07	-0.26	-0.14	0.00	0.07	0.02
MTRIE	-0.47	-0.07	-0.44	0.22	0.00	0.19
MTRPT	-0.25	-0.29	-0.02	0.06	0.08	0.00
PCEBE	-0.19	-0.38	0.06	0.04	0.15	0.00
PCEIE	-0.48	-0.05	-0.19	0.23	0.00	0.04
PCEPT	-0.26	-0.29	0.09	0.07	0.08	0.01
PIHDE	-0.03	-0.06	-0.10	0.00	0.00	0.01
PIHPT	-0.01	0.06	-0.01	0.00	0.00	0.00
RSLFI	-0.30	-0.20	-0.20	0.09	0.04	0.04
RSLIT	0.01	-0.04	0.04	0.00	0.00	0.00
RSLPT	0.01	-0.17	0.23	0.00	0.03	0.05
WINBE	0.12	-0.32	0.24	0.01	0.10	0.06
WINFI	0.26	-0.44	-0.06	0.07	0.19	0.00
WINNL	-0.06	-0.16	0.16	0.00	0.02	0.03
XTRBE	-0.06	-0.21	-0.19	0.00	0.04	0.04
XTRIE	-0.41	-0.08	-0.46	0.17	0.01	0.21
XTRPT	-0.17	-0.35	-0.31	0.03	0.12	0.09

Coding for the variables consists of five characters, three for the concept portrayed by the variable and two for the country. Thus, variable CPIAT stands for concept CPI (consumer price index) for country AT (Austria). The acronyms used in the table are explained below. (One important point to keep in mind is that the concept sometimes differs across countries, and this entails a rather loose labelling for the variables.)

Countries

AT:	Austria
BE:	Belgium
DE:	Germany
ES:	Spain
FI:	Finland
FR:	France
IE:	Ireland
IT:	Italy
NL:	Netherlands
PT:	Portugal

Concepts

Balanced-panel variables

CPI: consumer price index
MTD: import deflator
PCD: private consumption deflator
PPI: producer's price index
XTD: export deflator
YED: GDP deflator
CAP: capacity utilisation
ERN: total earnings
HST: housing starts
LFN: labour force
LNN: total employment
LTI: long-term interest rate
MFB: manufacturing book orders
MFS: level of stocks in manufacturing
MTR: total imports
PCE: private consumer expenditure
PIH: housing permits
RSL: retail sales
STI: short-term interest rate
UNR: unemployment rate
WIN: total compensation of employees
XTR: total imports

Unbalanced-panel variables

ULC: unit labour costs
M1: M1
M2: M2
M3: M3
MFO: new orders in manufacturing

Appendix B:
A discussion on the forecasting framework

As stated in the main text, forecast regressions are based on (B.1), which is expression (4.1) repeated here for convenience. As before, y_t is the variable of interest, assumed to be I(1), z_t is the indicator variable being tested, assumed to be I(0), and ε_t is a well behaved error term, while h stands for the number of periods ahead for which the forecast has to be performed. An explicit model for z_t may be summarised by (B.2), in which a (stochastic) relationship is assumed to exist between that variable and variable x_t. The latter is a vector variable that may contain lags of z_t and lagged values of Δy_t, but which in general will be considered to contain supplementary information.[14] Obviously, variable z_t is assumed to be impossible to forecast with perfect accuracy.

$$\frac{y_{t+h} - y_t}{h} = A(L) \cdot \Delta y_t + B(L) \cdot z_t + \varepsilon_t \tag{B.1}$$

$$z_t = \Phi(x_t) \tag{B.2}$$

As already expressed in the main text, expression (B.1) is non-recursive in that all information needed to derive an h-step-ahead forecast is available at time t. Instead, the normal forecasting practice starts from a recursive system like (B.3), a repetition of (4.2) in the main text. A professional forecaster would thus draw a forecast by recursing on (B.3) and (B.2), and would probably be willing to expend some effort in fine-tuning his/her view of the future evolution of z_t, based on the assessment made for x_t.

$$\Delta y_{t+1} = A(L) \cdot \Delta y_t + B(L) \cdot z_t + \varepsilon_t \tag{B.3}$$

Expressions (B.4) and (B.5) express how h-step-ahead forecasts are obtained with the two approaches. One notable difference between the two expressions is the presence of expectations on the right-hand side of the recursive system, and their absence in the non-recursive one (hence their name).

$$E_t \frac{y_{t+h} - y_t}{h} = A(L) \cdot \Delta y_t + B(L) \cdot z_t \tag{B.4}$$

$$E_t \Delta y_{t+h} = A(L) \cdot E_t \Delta y_{t+h-1} + B(L) \cdot E_t z_{t+h-1} \tag{B.5}$$

One problem with (B.4) is that it does not clearly define what is the data generating process for z_t, and thus skips entirely the information that could be gained with (B.2). Obviously, if z_t only depends on its own lags and lagged values of y_t there is a one-to-one mapping between (B.4) and (B.5), but if the variable is explained by other variables then necessarily (B.4) lacks information. This can be seen intuitively by noting that $E_t z_{t+h-1}$ only depends, in the latter case, on contemporaneous and lagged values of z_t and Δy_t, all of which already enter (B.4). However, if (B.2) contains extraneous information, the forecasting equation (B.4) will miss relevant regressors. Further to that, it is widely believed that observations h-periods apart are less related than contiguous observations, and this may reduce the significance of the estimated parameters in (B.4), and increase the volatility of the forecast. On the other hand, it has to be admitted that the single-step forecast of (B.4) minimises the effect of errors in the model specification, as these are not propagated to periods in between, as is the case in (B.5). It is very difficult to assess formally the relative importance of all these factors, as they involve testing the out-of-sample robustness of the models, a task for which standard in-sample tests may fail to give a proper answer.

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[14] It could also contain contemporaneous values of Δy_t without affecting results, although this would compromise the use of z_t in forecasting.

All in all, it is difficult to decide a priori whether (B.1) or (B.3) is preferable as a forecasting device. This paper has opted for (B.1) not just because it is now widely accepted, but rather because we do not feel comfortable specifying a generating model for the indicators on which we will focus: dynamic factors extracted from a rich dataset.[15] For us, expression (B.1) presents the convenient advantage of not requiring this information. Nonetheless, a number of tests were performed to ensure that the forecasting ability of (B.1) in normal circumstances matches that of (B.3). Thus, loosely speaking, our null hypothesis is that (B.1) is not worse in forecasting than (B.3). Unfortunately, the test cannot be treated explicitly as a standard one, because our centre of interest is the robustness of each system in the face of unforeseen structural breaks, and on this econometrics does not yet have much to say; see, for example Clements and Hendry (1998). The test loosely proposed is thus explicitly one of out-of-sample robustness in the sample under analysis. Instead, a relatively large number of tests were run in which either (B.1) or (B.3) was slightly changed, as local alternatives to the original system, and forecasting tests were run. The relevance of this step lies in the fact that a *consistently* worse performance of (B.1) would make the forecasting tests included in the rest of the paper almost irrelevant.

A number of out-of-sample exercises were run with inflation measured by the HICP and, where required, GDP as an indicator. GDP was chosen as an indicator for the bivariate system below because the inflation-output system is fairly standard in the literature and known to work relatively well: as a benchmark, correspondingly, it may bias results against the non-recursive system, which is the system being tested. In all the systems, the equation for GDP played the role of (B.2). Both variables were in logs, GDP also in the first difference. In each test, the system was changed to homogenise the variables forecast by the two equations, in ways described below.

Test 1. Standard recursive system against re-expressed non-recursive system

In the first test, (B.4) was changed into (B.4') and tested against (B.5). When GDP was used as an indicator, the recursive system was a VAR with inflation and output. In this guise, both the recursive and the non-recursive system modelled the first difference of HICP.

$$E_t \Delta y_{t+h} = A(L) \cdot \Delta y_t + B(L) \cdot z_t \tag{B.4'}$$

Test 2. Re-expressed recursive system against standard non-recursive system

The second test changed the definition of (B.5) in order for it to model the same variable as (B.4), as in (B.5'). Expression (B.5') is nothing but a standard one-step-ahead recursive equation modelling the same variable as (B.1).

$$E_t \frac{y_{t+h} - y_t}{h} = A(L) \cdot E_t \frac{y_{t+h-1} - y_{t-1}}{h} + B(L) \cdot E_t z_{t+h-1} \tag{B.5'}$$

Test 3. Cumulated recursive forecasts against standard non-recursive forecasts

The third test took (B.4) and (B.5) unchanged, but cumulated the *h*-recursive forecasts of (B.5) in order to match the variable generated by (B.4).

Test 4. Differenced non-recursive forecasts against standard recursive forecasts

Finally, the fourth test also used (B.4) and (B.5) unchanged, but took first differences of the forecasts generated by the non-recursive system to match the variable generated by (B.5).[16]

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15 In other words, factors are meant to be able to replace all variables that could appear in (B.1) with no significant loss of information. Under this assumption, (B.2) contains no relevant forecasting information and can thus be ignored.

16 More precisely, calling $\Delta_h y_{t+h} \equiv y_{t+h} - y_t$, the forecast is $E_t \Delta_h y_{t+h} - E_t \Delta_{h-1} y_{t+h-1}$.

Table 1

Recursive and non-recursive systems
Relative performance

	Steps ahead							
	1		2		3		4	
Test 1: standard recursive forecast against non-standard non-recursive forecast								
Univariate	1.00	(0.00)	0.98	(0.20)	0.95	(0.41)	0.90	(0.52)
Bivariate	1.00	(0.00)	0.99	(0.11)	0.97	(0.28)	0.99	(0.29)
Test 2: non-standard recursive forecast against standard non-recursive forecast								
Univariate	1.00	(0.00)	1.00	(0.09)	1.05	(0.26)	1.06	(0.17)
Bivariate	1.00	(0.00)	1.01	(0.08)	1.12	(0.38)	1.15	(0.19)
Test 3: cumulation of recursive forecasts against non-recursive forecast								
Univariate	1.00	(0.00)	0.98	(0.20)	0.92	(0.41)	0.87	(0.55)
Bivariate	1.00	(0.00)	1.01	(0.11)	0.99	(0.30)	1.00	(0.32)
Test 4: recursive forecast against decumulated non-recursive forecasts								
Univariate	1.00	(0.00)	0.99	(0.20)	0.94	(0.41)	0.88	(0.55)
Bivariate	1.00	(0.00)	1.00	(0.11)	0.96	(0.30)	0.98	(0.32)

NB A value lower than one indicates the recursive system is to be preferred.

Table 1 collects the relative size of the RMSE of the one-step-ahead to four-steps-ahead forecasts of the chosen non-recursive system compared with the more standard recursive one, for both the univariate (ie inflation-only) system and the bivariate one (ie inflation and output).[17] A number lower than one in a particular cell means that the recursive system is to be preferred, and the converse in the other case.[18] Standard errors for the ratios, reported between parentheses, are a delta-method first-order approximation to the variance of the ratio, corrected for heteroskedasticity and autocorrelation using the Newey-West non-parametric method. Although the evidence on the relative merits of both equations is mixed, results shown lend support to our claim that (B.4) is an appropriate tool for the exercise concerned.

[17] The forecasting equations used in Table 1 included four lags of inflation and, where applicable, output.

[18] By construction, the ratio for the one-step-ahead forecasts is one.

Appendix C:
Description of data

A total of 35 series per country were considered for the creation of the dataset. The dataset comprises: real variables, national account deflators, and different prices, monetary and credit variables, interest rates, labour statistics, and inventories of finished and ordered manufactured goods. Only 68% of the total data are available for the 10 countries analysed over the sample period of 1970 Q1 to 2000 Q3 (see the following Table). Going beyond this overall picture, the following points can be made:

1. The countries for which severe problems arise in terms of availability are Austria, Germany, Ireland, and Portugal, countries for which almost half of the series are not available. For Germany the problem arises from the lack of data for “Germany as a whole” prior to 1991 for most series (the total share of available data is only 57%). Data for Ireland are mostly annual, while for Austria and Portugal the starting dates for many series are only 1985 and 1998. Also worth mentioning is Belgium, for which some series start only in 1985.

2. Some series are not available for all countries; for example wholesale sales data are available only for France and Finland. Housing starts data, which cover 18%, are available for Belgium, Germany, Spain, France, the Netherlands, Austria and Finland. Data on credit to non-financial institutions and to individuals (21.9% and 25.4% covering sample respectively) are available only for Belgium, Germany and France, and for a very short time span as well. WPI (33.6%) is available only for Germany, Ireland, Italy, Austria and Finland. Unit labour costs are covered by only 40% (no data are available for Ireland, Austria or Portugal, and German data start in 1991 Q1).

3. Some series are available only with annual frequencies for many countries, such as labour force, and others, namely long-term interest rates, have late starting dates (after 1986) for all countries except Belgium and Spain (after 1978).

4. Finally, there is also a timeliness problem, ie not all countries have yet published data for all series for 2000 Q3; also some series are drawn from annual data, and therefore the latest observation is 1999. Very few countries in the BIS database are still publishing credit data; however, the latest observations are 1999 Q3 for Germany and 1998 Q4 for Belgium. Data on permits issued also lag behind a bit (1999 Q4 Germany, Spain and Ireland).

Series	Countries								
	Belgium			Germany			Spain		
	Availability	Observations	Coverage(a)	Availability	Observations	Coverage(a)	Availability	Observations	Coverage(a)
Ind'l Production Total (OECD, MEI)	70q1-99q1	**117**	**99%**	70q1-99q1	**117**	**99%**	70q1-99q1	**117**	**99%**
Capacity Utilization (EC Surveys and OECD, MEI*)	73q1-99q2	**106**	**90%**	80q1-99q2	**78**	**66%**	70q1-99q2*	**118**	**100%**
GDP (OECD, QNA and BIS*)	85q1-99q2	**61**	**52%**	91q1-99q1(b)	**34**	**29%**	70q1-99q2	**118**	**100%**
Labour Force (OECD, Labour Stats. and BIS*)	70q1-98q4	**29**	**25%**	70q1-98q4	**29**	**25%**	70q1-99q2*	**118**	**100%**
Employment (OECD, Labour Stats. and BIS*)	85q1-99q1*	**57**	**48%**	91q1-99q1(b)*	**33**	**28%**	70q1-99q1*	**117**	**99%**
Unemployment Rate (BIS)	70q1-99q2	**118**	**100%**	92q1-99q2(b)	**30**	**25%**	70q1-99q2	**118**	**100%**
Retail Sales (OECD, MEI)	76q1-99q2	**94**	**80%**	70q1-99q2	**118**	**100%**	95q1-99q2	**18**	**15%**
Wholesale Sales (OECD, MEI)			**0%**			**0%**			**0%**
Personal Consumption Expenditure (OECD, QNA)	85q1-99q2	**61**	**52%**	92q1-99q2(b)	**34**	**29%**	70q1-99q2	**118**	**100%**
Housing Starts, Construction put in place (OECD, MEI)	70q1-99q1	**117**	**99%**	91q1-99q1	**33**	**28%**	72q1-99q2	**110**	**93%**
Permits Issued (OECD, MEI)	70q1-99q1	**117**	**99%**	79q1-99q2	**82**	**69%**	92q1-99q2	**30**	**25%**
Stocks of finished goods in manufacturing, Survey Assessme	70q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**	87q1-99q2	**50**	**42%**
Orders in manufacturing, Survey Assessment (EC Survey)	70q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**	87q1-99q2	**50**	**42%**
Book Orders, Survey Assessment (EC Survey)	70q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**	87q1-99q2	**50**	**42%**
Effective Exchange Rate (ECB Database)	83q4-99q2	**66**	**56%**	83q4-99q2	**66**	**56%**	83q4-99q2	**66**	**56%**
Short-Term Interest Rates (Derived ECB database, and AMECO	91q1-99q2(c)	**34**	**29%**	70q2-99q2	**118**	**100%**	77q2-99q2	**118**	**100%**
Long-Term Interest Rates (Derived ECB database)	78q1-99q2(c)	**86**	**73%**	91q1-99q2(c)	**34**	**29%**	78q3-99q2(c)	**86**	**73%**
Money Stock M1 (ECB database)	80q2-99q2	**78**	**66%**	80q2-99q2	**78**	**66%**	80q2-99q2	**78**	**66%**
Money Stock M2 (ECB database)	80q2-99q2	**78**	**66%**	80q2-99q2	**78**	**66%**	80q2-99q2	**78**	**66%**
Money Stock M3 (ECB database)	80q2-99q2	**78**	**66%**	80q2-99q2	**78**	**66%**	80q2-99q2	**78**	**66%**
Credit to non financial institutions (BIS)	80q1-98q4	**76**	**64%**	70q1-97q3	**110**	**93%**			**0%**
Credit to Individuals (BIS)	80q1-98q4	**76**	**64%**	70q2-97q4	**111**	**94%**			**0%**
PPI Finished goods (OECD, MEI, and ECB database*)	80q1-99q2	**78**	**66%**	70q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**
WPI (ECB database* and BIS**)			**0%**	91q1-99q2*	**34**	**29%**			**0%**
CPI (OECD, MEI)	70q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**
Private Cons.Deflator (OECD, QNA)	85q1-99q2	**58**	**49%**	92q1-99q2(b)	**34**	**29%**	70q1-99q2	**118**	**100%**
GDP deflator (OECD, QNA)	85q1-99q2	**58**	**49%**	92q1-99q2(b)	**34**	**29%**	70q1-99q2	**118**	**100%**
Government Consumption Deflator (OECD, QNA)	85q1-99q2	**58**	**49%**	91q1-99q2	**34**	**29%**	70q1-99q2	**118**	**100%**
Gross fixed capital formation Deflator (OECD, QNA)	85q1-99q2	**58**	**49%**	91q1-99q2	**34**	**29%**	70q1-99q2	**118**	**100%**
Exports Deflator (OECD, QNA)	85q1-99q2	**58**	**49%**	92q1-99q2(b)	**34**	**29%**	70q1-99q2	**118**	**100%**
Imports Deflator (OECD, QNA)	85q1-99q2	**58**	**49%**	92q1-99q2(b)	**34**	**29%**	70q1-99q2	**118**	**100%**
Compensation of Employees (OECD,QNA)	85q1-99q2	**58**	**49%**	92q1-99q2(b)	**34**	**29%**	95q1-99q2	**118**	**100%**
Hourly Earnings (OECD, MEI)	80q1-99q2	**78**	**66%**	70q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**
Real Exports (OECD, QNA)	85q1-99q2	**58**	**49%**	92q1-99q2(b)	**34**	**29%**	70q1-99q2	**118**	**100%**
Real Imports (OECD, QNA)	85q1-99q2	**58**	**49%**	92q1-99q2(b)	**34**	**29%**	70q1-99q2	**118**	**100%**
ULC (BIS)	85q1-99q2	**58**	**49%**	92q1-99q2(b)	**34**	**29%**	70q1-99q2	**118**	**100%**
TOTAL 35 Series		**2657**	**64%**		**2343**	**57%**		**3170**	**77%**

(a) Coverage stands for the ratio between available data and total number of observations.

(b) Data for Germany is available in most cases only as of 1991, however it is possible to obtain longer series by rescaling and joining to Western Germany series.

(c) Some series have been rescalled and linked to other series as done to solve the German Unification issue and to have series that go as far as 1970.

e.g.This was done for Long - term and Short-term interest rates using AMECO annual data for past data.

Series	Countries								
	France			Ireland			Italy		
	Availability	Observations	Coverage(a)	Availability	Observations	Coverage(a)	Availability	Observations	Coverage(a)
Ind'l Production Total (OECD, MEI)	70q1-99q1	**117**	**99%**	75q3-99q2	**98**	**83%**	70q1-99q1	**117**	**99%**
Capacity Utilization (EC Surveys and OECD, MEI*)	76q1-99q2	**94**	**80%**	76q1-99q2*	**94**	**80%**	70q1-99q2	**118**	**100%**
GDP (OECD, QNA and BIS*)	70q1-99q2	**118**	**100%**	75q1-97q4*	**24**	**20%**	70q1-99q2	**118**	**100%**
Labour Force (OECD, Labour Stats. and BIS*)	70q1-99q2*	**118**	**100%**	70q1-97q4	**28**	**24%**	70q1-99q2*	**118**	**100%**
Employment (OECD, Labour Stats. and BIS*)	70q1-98q4	**29**	**25%**	70q1-97q4	**28**	**24%**	70q1-99q1*	**119**	**101%**
Unemployment Rate (BIS)	70q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**
Retail Sales (OECD, MEI)	75q1-99q2	**98**	**83%**	70q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**
Wholesale Sales (OECD, MEI)	70q1-99q2	**118**	**100%**			**0%**			**0%**
Personal Consumption Expenditure (OECD, QNA)	70q1-99q2	**118**	**100%**	75q1-97q4*	**23**	**19%**	70q1-99q2	**118**	**100%**
Housing Starts, Construction put in place (OECD, MEI)	70q1-99q1	**117**	**99%**			**0%**			**0%**
Permits Issued (OECD, MEI)	70q1-99q1	**117**	**99%**	92q1-99q2	**30**	**25%**			**0%**
Stocks of finished goods in manufacturing, Survey Assessme	70q1-99q2	**118**	**100%**	75q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**
Orders in manufacturing, Survey Assessment (EC Survey)	70q1-99q2	**118**	**100%**	75q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**
Book Orders, Survey Assessment (EC Survey)	70q1-99q2	**118**	**100%**	75q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**
Effective Exchange Rate (ECB Database)	83q4-99q2	**66**	**56%**	83q4-99q2	**66**	**56%**	83q4-99q2	**66**	**56%**
Short-Term Interest Rates (Derived ECB database, and AMECO	72q1-99q2(b)	**118**	**100%**	72q1-99q2(b)	**82**	**69%**	72q1-99q2(b)	**78**	**66%**
Long-Term Interest Rates (Derived ECB database)	88q1-99q2(b)	**50**	**42%**	88q1-99q2(b)	**42**	**36%**	88q1-99q2(b)	**102**	**86%**
Money Stock M1 (ECB database)	80q2-99q2	**78**	**66%**	80q2-99q2	**78**	**66%**	80q2-99q2	**78**	**66%**
Money Stock M2 (ECB database)	80q2-99q2	**78**	**66%**	80q2-99q2	**78**	**66%**	80q2-99q2	**78**	**66%**
Money Stock M3 (ECB database)	80q2-99q2	**78**	**66%**	80q2-99q2	**78**	**66%**	80q2-99q2	**78**	**66%**
Credit to non financial institutions (BIS)	78q1-98q4	**84**	**71%**			**0%**			**0%**
Credit to Individuals (BIS)	78q1-98q4	**84**	**71%**			**0%**	89q3-99q2	**42**	**36%**
PPI Finished goods (OECD, MEI, and ECB database*)	70q1-99q2	**118**	**100%**	85q1-99q2*	**58**	**49%**	81q1-99q2	**114**	**97%**
WPI (ECB database and BIS*)			**0%**	70q1-99q1*	**117**	**99%**	89q1-98q4**	**116**	**98%**
CPI (OECD, MEI)	70q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**
Private Cons.Deflator (OECD, QNA)	70q1-99q2	**118**	**100%**	75q1-97q4*	**23**	**19%**	70q1-99q2	**118**	**100%**
GDP deflator (OECD, QNA)	70q1-99q2	**118**	**100%**	75q1-97q4*	**23**	**19%**	70q1-99q2	**118**	**100%**
Government Consumption Deflator (OECD, QNA)	70q1-99q2	**118**	**100%**	75q1-97q4*	**23**	**19%**	70q1-99q2	**118**	**100%**
Gross fixed capital formation Deflator (OECD, QNA)	70q1-99q2	**118**	**100%**	75q1-97q4*	**23**	**19%**	70q1-99q2	**118**	**100%**
Exports Deflator (OECD, QNA)	70q1-99q2	**118**	**100%**	75q1-97q4*	**23**	**19%**	70q1-99q2	**118**	**100%**
Imports Deflator (OECD, QNA)	70q1-99q2	**118**	**100%**	75q1-97q4*	**23**	**19%**	70q1-99q2	**118**	**100%**
Compensation of Employees (OECD,QNA)	70q1-99q2	**118**	**100%**	75q1-97q4*	**23**	**19%**	70q1-99q2	**118**	**100%**
Hourly Earnings (OECD, MEI)	70q1-99q2	**118**	**100%**	75q1-99q2*	**118**	**100%**	70q1-99q2	**118**	**100%**
Real Exports (OECD, QNA)	70q1-99q2	**118**	**100%**	75q1-97q4*	**23**	**19%**	70q1-99q2	**118**	**100%**
Real Imports (OECD, QNA)	70q1-99q2	**118**	**100%**	75q1-97q4*	**23**	**19%**	70q1-99q2	**118**	**100%**
ULC (BIS)	78q1-99q2	**86**	**73%**				82q1-99q2	**70**	**59%**
TOTAL 35 Series		**3654**	**88%**		**1957**	**47%**		**3418**	**83%**

(a) Coverage stands for the ratio between available data and total number of observations.

(b) Some series have been rescalled and linked to other series as done to solve the German Unification issue and to have series that go as far as 1970.

e.g.This was done for Long-term and Short-term interest rates using AMECO annual data for past data.

Quarterly data for Ireland for some series has been interpolated from annual data. (GDP, labour force, employment, personal consumption, all deflators, imports and exports).

Series	Countries								
	Netherlands			Austria			Portugal		
	Availability	Observations	Coverage(a)	Availability	Observations	Coverage(a)	Availability	Observations	Coverage(a)
Ind'l Production Total (OECD, MEI)	70q1-99q1	**117**	**99%**	70q1-99q1	**117**	**99%**	70q1-99q1	**117**	**99%**
Capacity Utilization (EC Surveys and OECD, MEI*)	71q1-99q2	**119**	**101%**	96q1-99q2	**19**	**16%**	77q1-99q2*	**90**	**76%**
GDP (OECD, QNA and BIS*)	77q1-99q2	**90**	**76%**	70q1-99q2	**118**	**100%**	88q1-98q4	**116**	**98%**
Labour Force (OECD, Labour Stats. and BIS*)	70q1-99q2*	**30**	**25%**	70q1-98q4	**29**	**25%**	70q1-98q4	**29**	**25%**
Employment (OECD, Labour Stats. and BIS*)	70q1-98q4*	**29**	**25%**	70q1-98q4	**29**	**25%**	70q1-99q1*	**119**	**101%**
Unemployment Rate (BIS)	70q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**
Retail Sales (OECD, MEI)	70q1-99q2	**118**	**100%**	73q1-99q2	**106**	**90%**	90q1-99q2	**38**	**32%**
Wholesale Sales (OECD, MEI)			**0%**			**0%**			**0%**
Personal Consumption Expenditure (OECD, QNA)	77q1-99q2	**90**	**76%**	70q1-99q2	**118**	**100%**	88q1-98q4	**116**	**98%**
Housing Starts, Construction put in place (OECD, MEI)	70q1-99q2	**118**	**100%**	96Q1-99q1	**13**	**11%**			**0%**
Permits Issued (OECD, MEI)	70q1-99q1	**118**	**100%**			**0%**	78q1-99q1	**85**	**72%**
Stocks of finished goods in manufacturing, Survey Assessme	72q1-99q2	**118**	**100%**	85q1-99q2	**58**	**49%**	87q1-99q2	**50**	**42%**
Orders in manufacturing, Survey Assessment (EC Survey)	72q1-99q2	**118**	**100%**	96q1-99q2	**14**	**12%**	87q1-99q2	**50**	**42%**
Book Orders, Survey Assessment (EC Survey)	72q1-99q2	**118**	**100%**	85q1-99q2	**58**	**49%**	87q1-99q2	**50**	**42%**
Effective Exchange Rate (ECB Database)	83q4-99q2	**66**	**56%**	83q4-99q2	**66**	**56%**	83q4-99q2	**66**	**56%**
Short-Term Interest Rates (Derived ECB database, and AMECO	72q1-99q2(b)	**110**	**93%**	72q1-99q2(b)	**38**	**32%**	72q1-99q2(b)	**38**	**32%**
Long-Term Interest Rates (Derived ECB database)	88q1-99q2(b)	**46**	**39%**	88q1-99q2(b)	**54**	**46%**	88q1-99q2(b)	**54**	**46%**
Money Stock M1 (ECB database)	80q2-99q2	**78**	**66%**	80q2-99q2	**78**	**66%**	80q2-99q2	**78**	**66%**
Money Stock M2 (ECB database)	80q2-99q2	**78**	**66%**	80q2-99q2	**78**	**66%**	80q2-99q2	**78**	**66%**
Money Stock M3 (ECB database)	80q2-99q2	**78**	**66%**	80q2-99q2	**78**	**66%**	80q2-99q2	**78**	**66%**
Credit to non financial institutions (BIS)			**0%**			**0%**			**0%**
Credit to Individuals (BIS)			**0%**			**0%**			**0%**
PPI Finished goods (OECD, MEI, and ECB database*)	76q1-99q2*	**94**	**80%**	70q1-99q2	**118**	**100%**	90q1-99q2*	**82**	**69%**
WPI (ECB database and BIS*)			**0%**	96q1-99q2**	**14**	**12%**			**0%**
CPI (OECD, MEI)	70q1-99q2	**118**	**100%**	76q1-99q2	**94**	**80%**	88q1-99q2	**46**	**39%**
Private Cons.Deflator (OECD, QNA)	77q1-99q2	**90**	**76%**	76q1-99q2	**94**	**80%**	88q1-98q4	**116**	**98%**
GDP deflator (OECD, QNA)	77q1-99q2	**90**	**76%**	76q1-99q2	**94**	**80%**	88q1-98q4	**116**	**98%**
Government Consumption Deflator (OECD, QNA)	77q1-99q2	**90**	**76%**	76q1-99q2	**94**	**80%**	88q1-98q4	**116**	**98%**
Gross fixed capital formation Deflator (OECD, QNA)	77q1-99q2	**90**	**76%**	76q1-99q2	**94**	**80%**	88q1-98q4	**116**	**98%**
Exports Deflator (OECD, QNA)	77q1-99q2	**90**	**76%**	76q1-99q2	**94**	**80%**	88q1-98q4	**116**	**98%**
Imports Deflator (OECD, QNA)	77q1-99q2	**90**	**76%**	76q1-99q2	**94**	**80%**	88q1-98q4	**116**	**98%**
Compensation of Employees (OECD,QNA)	77q1-99q2	**90**	**76%**	70q1-99q2	**118**	**100%**			**0%**
Hourly Earnings (OECD, MEI)	70q1-99q2	**118**	**100%**	70q1-99q2	**118**	**100%**			**0%**
Real Exports (OECD, QNA)	77q1-99q2	**90**	**76%**	76q1-99q2	**94**	**80%**	88q1-98q4	**116**	**98%**
Real Imports (OECD, QNA)	77q1-99q2	**90**	**76%**	76q1-99q2	**94**	**80%**	88q1-98q4	**116**	**98%**
ULC (BIS)	84q1-99q2	**65**	**55%**			**0%**			**0%**
TOTAL 35 Series		**2962**	**72%**		**2403**	**58%**		**2426**	**59%**

(a) Coverage stands for the ratio between available data and total number of observations.

(b) Some series have been rescalled and linked to other series as done to solve the German Unification issue and to have series that go as far as 1970.

e.g.This was done for Long-term and Short-term interest rates using AMECO annual data for past data.

Series	Finland		
	Availability	Observations	Coverage(a)
	70q1-99q1	117	0.99152542
Ind'l Production Total (OECD, MEI)	80q1-99q2	83	70%
Capacity Utilization (EC Surveys and OECD, MEI*)	75q1-99q2	98	83%
GDP (OECD, QNA and BIS*)	70q1-99q2*	118	100%
Labour Force (OECD, Labour Stats. and BIS*)	70q1-99q1*	117	99%
Employment (OECD, Labour Stats. and BIS*)	70q1-99q2	118	100%
Unemployment Rate (BIS)	85q1-99q2	58	49%
Retail Sales (OECD, MEI)	75q1-99q1	97	82%
Wholesale Sales (OECD, MEI)	75q1-99q2	98	83%
Personal Consumption Expenditure (OECD, QNA)	70q1-99q1	117	99%
Housing Starts, Construction put in place (OECD, MEI)	70q1-99q1	117	99%
Permits Issued (OECD, MEI)	93q1-99q2	26	22%
Stocks of finished goods in manufacturing, Survey Assessme	85q1-99q2	58	49%
Orders in manufacturing, Survey Assessment (EC Survey)	85q1-99q2	58	49%
Book Orders, Survey Assessment (EC Survey)	83q4-99q2	66	56%
Effective Exchange Rate (ECB Database)	90q1-99q2(b)	46	39%
Short-Term Interest Rates (Derived ECB database, and AMECO	86q1-99q2(b)	38	32%
Long-Term Interest Rates (Derived ECB database)	80q2-99q2	78	66%
Money Stock M1 (ECB database)	80q2-99q2	78	66%
Money Stock M2 (ECB database)	80q2-99q2	78	66%
Money Stock M3 (ECB database)			0%
Credit to non financial institutions (BIS)			0%
Credit to Individuals (BIS)	70q1-99q2	118	100%
PPI Finished goods (OECD, MEI, and ECB database*)	70q1-99q2**	118	100%
WPI (ECB database and BIS*)	70q1-99q2	118	100%
CPI (OECD, MEI)	75q1-99q2	98	83%
Private Cons.Deflator (OECD, QNA)	75q1-99q2	98	83%
GDP deflator (OECD, QNA)	75q1-99q2	98	83%
Government Consumption Deflator (OECD, QNA)	75q1-99q2	98	83%
Gross fixed capital formation Deflator (OECD, QNA)	75q1-99q2	98	83%
Exports Deflator (OECD, QNA)	75q1-99q2	98	83%
Imports Deflator (OECD, QNA)	70q1-99q2	118	100%
Compensation of Employees (OECD,QNA)	70q1-99q2	118	100%
Hourly Earnings (OECD, MEI)	75q1-99q2	98	83%
Real Exports (OECD, QNA)	75q1-99q2	98	83%
Real Imports (OECD, QNA)	89q1-99q2	42	36%
ULC (BIS)		3080	75%
TOTAL 35 Series		3084	75%

(a) Coverage stands for the ratio between available data and total number of observations.

(b) Some series have been rescalled and linked to other series as done to solve the German Unification issue and to have series that go as far as 1970. e.g.This was done for Long-term and Short-term interest rates using AMECO annual data for past data.

Series	Total Coverage[a] For Each Variable
Ind'l Production Total (OECD, MEI)	97.54%
Capacity Utilization (EC Surveys and OECD, MEI*)	77.88%
GDP (OECD, QNA and BIS*)	75.85%
Labour Force (OECD, Labour Stats. and BIS*)	54.75%
Employment (OECD, Labour Stats. and BIS*)	57.37%
Unemployment Rate (BIS)	92.54%
Retail Sales (OECD, MEI)	74.92%
Wholesale Sales (OECD, MEI)	18.22%
Personal Consumption Expenditure (OECD, QNA)	75.76%
Housing Starts, Construction put in place (OECD, MEI)	52.97%
Permits Issued (OECD, MEI)	58.98%
Stocks of finished goods in manufacturing, Survey Assessme	75.59%
Orders in manufacturing, Survey Assessment (EC Survey)	74.58%
Book Orders, Survey Assessment (EC Survey)	78.31%
Effective Exchange Rate (ECB Database)	55.93%
Short-Term Interest Rates (Derived ECB database, and AMECO	66.10%
Long-Term Interest Rates (Derived ECB database)	50.17%
Money Stock M1 (ECB database)	66.10%
Money Stock M2 (ECB database)	66.10%
Money Stock M3 (ECB database)	66.10%
Credit to non financial institutions (BIS)	22.88%
Credit to Individuals (BIS)	26.53%
PPI Finished goods (OECD, MEI, and ECB database*)	86.10%
WPI (ECB database and BIS*)	33.81%
CPI (OECD, MEI)	91.86%
Private Cons.Deflator (OECD, QNA)	73.47%
GDP deflator (OECD, QNA)	73.47%
Government Consumption Deflator (OECD, QNA)	73.47%
Gross fixed capital formation Deflator (OECD, QNA)	73.47%
Exports Deflator (OECD, QNA)	73.47%
Imports Deflator (OECD, QNA)	73.47%
Compensation of Employees (OECD,QNA)	67.37%
Hourly Earnings (OECD, MEI)	86.61%
Real Exports (OECD, QNA)	73.47%
Real Imports (OECD, QNA)	73.47%
ULC (BIS)	40.08%
TOTAL Coverage of the 35 Series	68%

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