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NOWCASTING EURO AREA ECONOMIC ACTIVITY IN REAL TIME: THE ROLE OF CONFIDENCE INDICATORS

Domenico Giannone,* Lucrezia Reichlin** and Saverio Simonelli***

This paper assesses the role of qualitative surveys for the early estimation of GDP in the Euro Area in a model-based automated procedure which exploits the timeliness of their release. The analysis is conducted using both an historical evaluation and a real-time case study on the current conjuncture.

Keywords: Forecasting; factor model; real-time data; large data sets; survey

JEL Classifications: E52; C33; C53

1. Introduction

The world economy has recently suffered the most severe recession in the postwar period.

Since the end of 2007 we have seen a prolonged period of consistently bad news coming from all the major macroeconomic releases. However, in recent months, signals have improved significantly. In the Euro Area these 'green shoots' have come mostly from qualitative survey data. Survey information is the most timely information on the current economic situation, available before industrial production and GDP. For this reason surveys are closely watched by forecasters. However, surveys are not 'hard data' since they convey information on firms' and consumers' sentiment and expectations, and there is no guarantee that they contain reliable information about GDP movements.

To understand whether these early signals based on surveys are really indicating that hard data like industrial production and GDP are improving, we need to assess their forecasting power for the hard data, namely GDP. Since timeliness is a key attribute of surveys, this has to be done on the basis of a model that takes into account the structure of information linked to the calendar of data releases, as described in Giannone, Reichlin, and Small (2008).

The first objective of this paper is to provide such an assessment on the basis of a simple vector autoregressive model (VAR) including quarterly GDP and monthly industrial production and surveys. The VAR is adapted to deal with mixed frequency (quarterly and monthly) data and different publication lags. We use the current conjuncture as a case study and produce a series of forecasts corresponding to the consecutive release of (real-time) data between April and September 2009.

A second objective of the paper is to consider a larger model, including disaggregated survey data, and evaluate the contribution to the forecast of this richer information. Given the size of the model, rather than using a VAR which demands the estimation of too many parameters, we use the factor model of Giannone, Reichlin, and Small (2008). This model facilitates consideration of a rich information set and retains parsimony.

The rest of the paper is organised as follows. The second section illustrates methodology and results for the aggregate surveys and, as mentioned, considers consecutive GDP forecasts for the third quarter of 2009, based on the release of real-time data between April and September 2009, as a case study. The third section describes the model and performs a historical evaluation of the role of disaggregated surveys for the forecasting of GDP. The fourth section concludes.

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Figure 1A. GDP quarter-on-quarter percentage changes

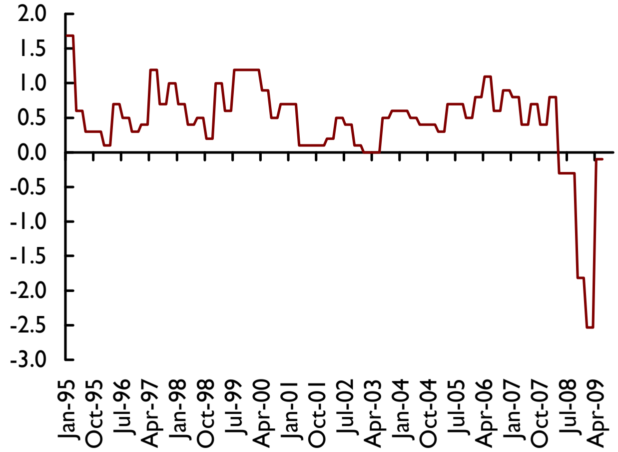


Figure 1B. Industrial production annual growth rate

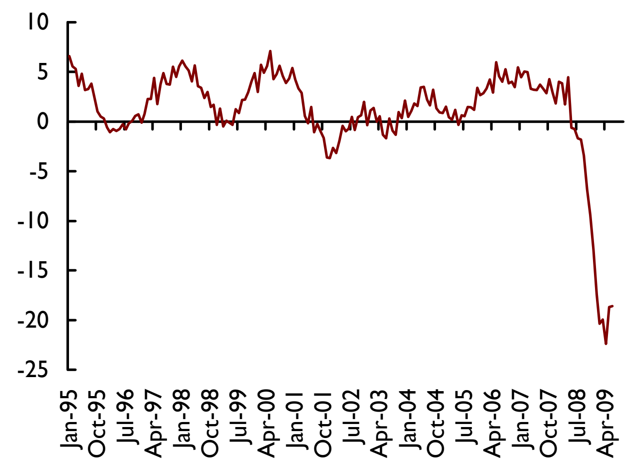
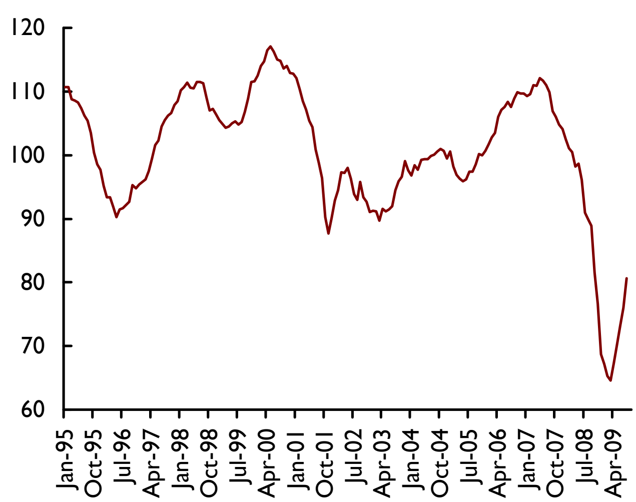


Figure 1C. Economic sentiment indicator from the surveys



2. The forecasts

The extraordinary depth of the recent recession in the Euro Area is evident from figure 1, where we plot the most recent (vintage) data for the quarterly growth rate of GDP, the annual growth rate of industrial production and the economic sentiment indicators since 1995.

Here we compute early estimates for GDP based on a vector autoregressive (VAR) model including these series. We study how macroeconomic prospects have evolved in recent months by estimating how GDP quarterly growth rate forecasts evolved as updated vintages of data became available each month from April to September 2009.

In order to replicate exactly the data which were available in real time, we use the vintages of data published in the different issues of the European Central Bank (ECB) Monthly Bulletin (MoBu). The data, collected and described by Giannone, Henry, Lalik, and Modugno (2009), represent a historical record of the summary information supplied to the public each month via the Monthly Bulletin, and to the ECB Governing Council at its first meeting of any given month.[1]

Publication dates and corresponding values of early

Table 1. Monthly Bulletin

Monthly Bulletin (2009)			Last available data		
Issue	Publication date	Cut-off date	GDP	IP (2009)	Survey (2009)
April	9 April	1 April	08Q4 (−1.5)	Jan. (−3.2)	March (64.6)
May	14 May	6 May	08Q4 (−1.6)	Feb. (−2.2)	April (67.2)
June	11 June	3 June	09Q1 (−2.5)	March (−1.6)	May (69.3)
July	9 July	1 July	09Q1 (−2.5)	April (−1.3)	June (73.3)
August	13 August	5 August	09Q1 (−2.5)	May (0.6)	July (76.0)
September	10 Sept.	2 Sept.	09Q2 (−0.1)	June (−0.5)	August (80.6)

Notes: The table reports the 2009 ECB Monthly Bulletins as follows: (a) the publication and cut-off date (in general, the cut-off date for the statistics included in the Monthly Bulletin is the day preceding the first meeting in the month of the ECB's Governing Council); (b) the last available data for GDP, Industrial Production and Surveys in the relative Monthly Bulletin. The numbers in brackets are the quarter-on-quarter percentage changes for GDP, the month-on-month percentage changes for industrial production and the economic sentiment indicator for the Surveys.

estimates of GDP, industrial production (IP) and surveys are reported in table 1. The April issue of the Monthly Bulletin contains data available on the ninth day of the month. On that date, the last available figure for GDP is the –1.5 per cent quarterly growth in 2008Q4 while the last available figure for industrial production is the –3.2 month-on-month percentage change registered in January 2009. The most up-to-date information is provided by the European Commission (EC) surveys which are available up to March. This indicator, in April, was at 64.6, well below the long-term average which is equal to 100.

GDP data for the first quarter of 2009 became available only at the June MoBu and showed a substantial decline, 2.5 per cent, with respect to the previous quarter.

Starting with the July MoBu, we got some positive signals coming from the economic sentiment indicator: 73 in June up from 69 in May. Survey data for July and August, published in the August and September MoBus respectively, showed further improvements.

This improving economic situation was partially confirmed with the release in the September MoBu of the GDP growth data for the second quarter of 2009. These data indicated a decline of –0.1 per cent, much less pronounced than the contraction in the first quarter. In fact, industrial production data are now (as of the time of writing) available up to June 2009 but do not appear to change the signal.

Let us now specify the model that will allow us to exploit all available information and produce short-term estimates for GDP growth. We use a vector autoregressive model since this is a flexible tool, able to capture rich linear dynamic interactions among the variables of interest. In order to deal with the flow of real-time information and publication lags, we have to consider data that have mixed, quarterly and monthly, frequency and 'jagged edges'. Therefore the standard VAR must be adapted to our problem.

We denote by $m_{0,t}$ the unobserved monthly growth rate of GDP and by $M_t = m_{1,t},\ldots,m_{k,t}$ a set of monthly predictors. Defining $X_t = (m_{0,t} M_t')'$, the VAR model is the following:

$$X_t = A_1 X_{t-1} + \ldots + A_p X_{t-p} + u_t \qquad (1)$$

Using the convention that a quarter is denoted by its final month, the unobserved monthly growth of GDP, $m_{0,t}$, is approximately related to the observed quarterly growth rate by the following relation:

$$y_t = (m_{0,t} + 2m_{0,t-1} + 3m_{0,t-2} + 2m_{0,t-3} + m_{0,t-4})/3 \qquad (2)$$

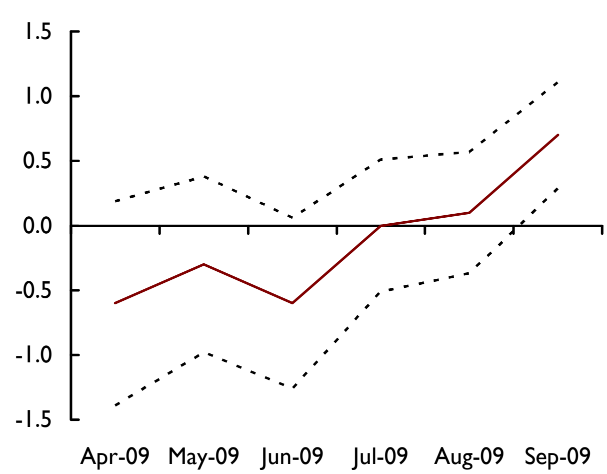
where y_t is observed every third month of the quarter.

If $m_{1,t},\ldots,m_{n,t}$ are observed, equations (1) and (2) can be cast in state space form and can be therefore be dealt with by Kalman filter techniques and the Expectation Maximization (EM) algorithm developed by Dempster and Rubin (1977).

This model is a generalisation of the bridge equations described in Baffigi, Golinelli, and Parigi (2004), Rünstler and Sédillot (2003) and Salazar and Weale (1999). Bridge equations essentially provide a means of relating quarterly data (GDP) to monthly data (typically surveys or industrial production) by taking quarterly aggregates of the monthly data and are the traditional models used in policy institutions for producing short-term forecasts.[2] The VAR, once adapted as described, generalises bridge equations since it allows for feedbacks from GDP to the predictors and explicitly takes into account the interaction among predictors.

Figure 2 reports the results for the short-term estimates of GDP growth in 2009Q3 produced by including as

Figure 2. GDP quarterly growth rate forecast for Q3-09



Note: The figure plots the forecast of the GDP quarterly growth rate for Q3-09, estimated as a function of the information contained in the monthly bulletin (x-axis). The forecast is obtained from the VAR model with GDP, industrial production and the economic sentiment indicator. The dashed lines report the 68 per cent confidence intervals, and are based on the historical accuracy of the forecasts.

predictors (M_t) the growth rate of industrial production and the Economic Sentiment indicators. The estimates are produced using the most recent set of five years data as they became available in each issue of the Monthly Bulletin from April to September. The number of lags p in the VAR is selected using the BIC criterion. We report point estimates and plus/minus one standard deviation of the forecast errors based on the out-of-sample historical performance of the model evaluated from the first quarter of 2002 onwards using the real-time database of Giannone, Henry, Lalik, and Modugno (2009). Under suitable assumptions, these are 68 per cent confidence bands.[3]

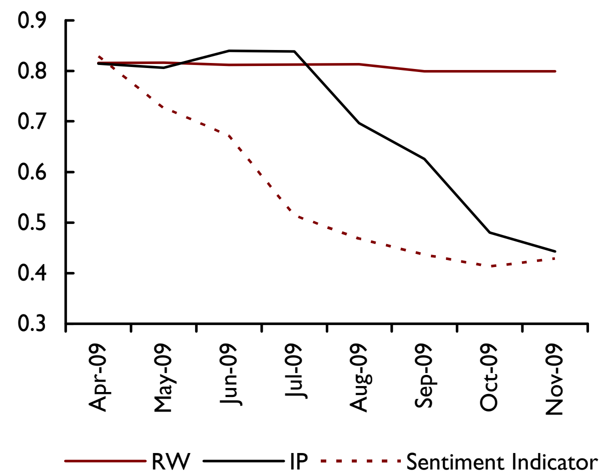
Results clearly show that the survey data published in July signalled a substantial improvement of the overall economy. In particular, the point estimates indicate positive growth in both July and September. Indeed the forecast in September is above the average growth rate experienced over the past five years (0.25 per cent). However, it would be informative to analyse the reliability of these predictions which have been produced using soft data. In order to perform this evaluation, we compare their real-time historical accuracy with respect to the forecasts using only industrial production, i.e. M_t including only the growth rate of industrial production. The measure of accuracy is the same as that used to define the confidence bands for figure 2. It is worth stressing that this is evaluated by looking at the historical accuracy of the forecasts produced by the models in out-of-sample experiments using real-time data as they became available in consecutive issues of the Monthly Bulletin from 2002 onwards.

Results are reported in figure 3. For comparability, we also report results for the accuracy of a naive benchmark. In the naive model, the GDP growth forecast is recursively set equal to the average GDP growth rate over the past five years.

The first striking result is that neither hard nor soft data are informative for the third quarter when forecasts are made in April. Neither surveys nor industrial production improve accuracy relative to the naive benchmark. When we move towards the reference quarter (2009Q3), the survey data and industrial production become informative. This is in line with Giannone, Reichlin, and Small (2008) who find that the bulk of predictability is at a very short horizon (nowcast).

Another clear pattern is that the forecasts from surveys tend to become more accurate earlier than those obtained with industrial production only. In July, the

Figure 3. Uncertainty around the forecast of GDP growth for 2009Q3



Note: The root-mean-square-forecast-error (RMSFE) estimates for GDP growth are shown as a function of the monthly information contained in the monthly bulletin (x-axis) and indicate, based on historical performance, how we have observed and expect the uncertainty associated with the forecast for 2009q3 shown in figure 2 to evolve as information accumulates. The figure plots the RMSFE for the naive model (red line), the VAR with GDP, Industrial Production and Economic Sentiment Indicator (dashed red line) and the VAR with GDP and Industrial Production (black line). RMSFE are computed by performing a real-time and out-of-sample forecasting exercise over the period 2001q1 until 2009q2.

first month of the third quarter, the forecast based on survey data is as accurate as a forecast produced in October using only industrial production. Further, the forecast, produced in September, is as accurate as the forecast that will be produced with industrial production in November, when two out of three months of industrial production are available. This implies that the model based on qualitative survey data only is able to produce forecasts which are as accurate as those based on hard data which are released much later in the quarter. Clearly, when a substantial amount of hard information regarding the quarter of interest becomes available, the advantage of survey-based forecasts disappears, indicating that the contribution of surveys to the forecast comes essentially from their timeliness.

These results lead us to the conclusion that, thanks to their timeliness, surveys provide valuable information and that therefore the early signals that they provide can be considered to be reliable indicators of economic conditions before hard indicators are released. This is also in line with the findings of Giannone, Reichlin, and Small (2008) for the United States, and Banbura and

Rünstler (2007), ECB (2008), Angelini, Camba-Méndez, Giannone, Rünstler, and Reichlin (2008) for the Euro Area.

3. The role of disaggregated survey information

The business and consumer surveys published in the ECB Monthly Bulletin are collected by the European Commission (Economic and Financial Affairs DG). The series are seasonally adjusted balances of opinion, i.e. constructed as the difference between the percentages of respondents giving positive and negative replies. Data are released at the end of the reference month. To be exact, we have (a) three manufacturing industry indicators;[4] (b) four consumer confidence indicators; (c) two construction confidence indicators; (d) three retail and trade confidence indicators; and (e) three service confidence indicators (see the appendix for details). Further, for each of these groups, sectoral confidence indicators are computed as simple averages of the indicators in the sector.[5] The economic sentiment indicator is constructed by averaging the sectoral confidence indicators. The industrial confidence indicator has a weight of 40 per cent, the services confidence indicator has a weight of 30 per cent, the consumer confidence indicator has a weight of 20 per cent and the two other indicators have a weight of 5 per cent each. The economic sentiment indicator is transformed to have a long-run average of 100.

In this section we will consider forecasts that use time series of surveys constructed from detailed disaggregated questions. The issue we want to address here is whether, by using more detailed information coming from sector specific questions, the accuracy of the early estimates can be improved.

The VAR model described above cannot be used with all the disaggregated information considered here because of the large estimation uncertainty induced by the proliferation of parameters to be estimated. To deal with this problem, Giannone, Reichlin, and Small (2008) proposed extracting common factors from the panel and regressing GDP on them ('bridging with factors'). The idea is to consider the monthly predictors as unobserved factors to be extracted from a set of observable monthly variables $\tilde{m}_{i,t}$ which are modeled as follows.

$$\tilde{m}_{i,t} = \lambda_i F_t + e_{i,t} i = 1,\ldots,n \tag{3}$$

where the idiosyncratic noise $e_{i,t}$ is assumed to be uncorrelated across variables and F_t and $e_{i,t}$ are orthogonal random variables for each i and at all leads and lags.

With this assumption, we can specify a VAR for $X_t = (m_{0,t}, M_t', F_t')'$.

In this VAR, we allow for different treatments of monthly predictors where some of them enter the VAR directly while others enter only through their common factors. Equations (1), (2) and (3) define a dynamic factor model which can be cast in a state space form. The model is estimated by Quasi Maximum Likelihood which can be computed using the EM algorithm. Doz, Giannone, and Reichlin (2006) have studied the asymptotic properties of QML estimation for large factor models (large n and large T) and have shown that the method is feasible and the estimates are robust to misspecification due to weak cross-sectional and serial correlation of the idiosyncratic errors. A similar strategy has been adopted recently by Banbura and Modugno (2009) who allow for arbitrary patterns of missing data. Unlike them, in this paper we allow for feedback from GDP to monthly factors.

Since the models are cast in a state space representation, dealing with the missing data at the end of sample is quite straightforward. As in Giannone, Reichlin, and Small (2008), we treat missing variables as random observations contaminated by extremely large measurement errors. This approach has been successfully applied to Euro Area data by Angelini, Camba-Méndez, Giannone, Rünstler, and Reichlin (2008) and by Banbura and Rünstler (2007).

An alternative approach for exploiting large information consists in averaging several forecasts, each based on a small number of predictors (see Kitchen and Monaco, 2003; Diron, 2006). For a comparison of the two methods (factor models and pooling) and a description of their use for short-term forecasting in the Euro Area, see the ECB Monthly Bulletin (2008) and Angelini, Camba-Méndez, Giannone, Rünstler, and Reichlin (2008). Here we consider both methods.

Table 2 reports the root mean square forecast error for the models estimated using industrial production and each of the disaggregated surveys. We also report the results when surveys are aggregated using the factor model, i.e. by estimating the model defined above where M_t is the growth rate of industrial production and $\tilde{m}_{i,t}$ are the survey indicators in all sectors. Finally, we also report results from pooling, i.e. the simple average of the forecasts produced by running many VARs, as described

Table 2. Root mean square forecast error

	July 2009	August 2009	Sept. 2009	Oct. 2009	Nov. 2009
Naive model	0.8	0.8	0.8	0.8	0.8
IP	0.8	0.7	0.6	0.5	0.4
Economic Sentiment indicator	0.5	0.5	0.4	0.4	0.4
Industrial CI	0.5	0.6	0.5	0.4	0.4
Order books	0.6	0.6	0.5	0.5	0.5
Stocks of finished product	0.7	0.7	0.6	0.5	0.5
Production expectation	0.6	0.5	0.5	0.4	0.4
Consumer CI	0.7	0.6	0.5	0.4	0.4
Financial situation over next 12 months	0.7	0.7	0.5	0.5	0.4
Economic situation over next 12 months	0.7	0.6	0.6	0.5	0.4
Unemployment situation over next 12 months	0.8	0.7	0.5	0.4	0.4
Saving situation over next 12 months	0.7	0.7	0.5	0.5	0.4
Construction CI	0.7	0.7	0.6	0.5	0.4
Order books	0.7	0.7	0.6	0.5	0.4
Employment expectation	0.7	0.6	0.5	0.4	0.4
Retail trade CI	0.8	0.7	0.6	0.5	0.4
Present business situation	0.8	0.7	0.6	0.5	0.5
Volume of stocks	0.8	0.7	0.6	0.5	0.4
Expected business situation	0.7	0.7	0.6	0.5	0.4
Service CI	0.7	0.6	0.5	0.4	0.4
Assessment of the business climate	0.7	0.6	0.6	0.5	0.4
Evolution of demand in recent months	0.7	0.6	0.6	0.5	0.4
Evolution of demand expected in the months ahead	0.7	0.6	0.5	0.4	0.4
Factor	0.6	0.5	0.5	0.4	0.4
Pooling	0.7	0.6	0.5	0.5	0.4

Note: The table reports the root mean square forecast error (RMSFE) for the naive model, the VAR with GDP, industrial production and each of the surveys at a time, pooling of all the disaggregated VAR (Pooling) and the VAR with GDP, industrial production and one common factor extracted from all surveys (Factor). The RMSFE estimates are shown, by column, as a function of the monthly information contained in consecutive MoBus and indicate, based on historical performance, how we have observed and expect the uncertainty associated with the forecast for 2009q3 to evolve as information accumulates.

in section 2, and including the growth rate of industrial production and each of the survey indicators as predictors M_t. The accuracy of the naive constant growth forecast, the forecast with industrial production only and those with industrial production and the economic sentiment indicator are reported for comparison.

Results indicate that none of the disaggregated surveys significantly improve on the forecasts produced using the economic sentiment indicator. We can hence conclude that disaggregated information on surveys does not increase forecast accuracy. In addition, extracting the factor from the disaggregated surveys does not improve significantly on simply using the aggregate produced by the European Commission.

4. Conclusion

This paper assesses the role of qualitative business surveys for the early estimation of GDP in the Euro Area in a model-based automated procedure which exploits the timeliness of data releases. The analysis is conducted using both an historical evaluation and a real-time case study on the current conjuncture.

Using an econometric model that can be automatically updated, we show that aggregate surveys produce an accurate early estimate of GDP. Moreover, considering two alternative estimation strategies, we show that sector-specific information does not provide a significant improvement in the reliability of these predictions.

NOTES

1 Eurostat started producing a chained linked GDP measure in 2005. For earlier vintages we use real GDP measured at constant prices.
2 The National Institute of Economic and Social Research, when nowcasting monthly GDP in the UK, uses an interpolation approach (to ensure the quarterly sum of the monthly GDP estimates is consistent with the observed quarterly estimate), which again uses monthly indicators; see Mitchell, Smith, Weale, Wright and Salazar (2005).
3 To be precise, we compute the root mean forecast errors of real-time and out-of-sample forecasts of GDP growth. For each quarter, the parameters of the model and the forecasts are estimated recursively (out-of-sample) using only the data that were available in the corresponding Monthly Bulletin issue (real time). For example, uncertainty for September is computed by considering forecasts based on the data available in the Monthly Bulletin issue of the third month of each reference quarter (the quarter for which the forecast of GDP growth is produced). Similarly uncertainty for April is relative to forecasts based on data available in the Monthly Bulletin issue of the first month of the quarter preceding the reference period. In order to maintain comparability of predictions along the evaluation sample, the model is always estimated using the most recent five years of data (rolling scheme) available at the date the forecast is computed. The evaluation period starts in January 2002, because for earlier vintages not all the surveys are available.
4 The industrial capacity utilisation indicator is not included since it is provided only at quarterly frequency.
5 The assessment of stocks and unemployment are used with inverted signs for the calculation of confidence indicators.

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APPENDIX

Release	Series	Transformation
Gross Domestic Product	Gross domestic product at constant prices	1
Industrial Production Index	Total industry excluding construction	2
Survey	Economic sentiment indicator	0
Industry Survey	Industrial confidence indicator	0
Industry Survey	Assessment of order-book levels	0
Industry Survey	Assessment of stocks of finished products	0
Industry Survey	Production expectations for the months ahead	0
Industry Survey	Production expectations for the months ahead	0
Consumer Survey	Consumer confidence indicator	0
Consumer Survey	Financial situation over next 12 months	0
Consumer Survey	General economic situation over next 12 months	0
Consumer Survey	Unemployment expectations over next 12 months	0
Consumer Survey	Savings over next 12 months	0
Construction Survey	Construction confidence indicator	0
Construction Survey	Assessment of order books	0
Construction Survey	Employment expectations for the months ahead	0
Retail Trade Survey	Retail confidence indicator	0
Retail Trade Survey	Present business situation	0
Retail Trade Survey	Assessment of stocks	0
Retail Trade Survey	Expected business situation	0
Service Survey	Service confidence indicator	0
Service Survey	Assessment of the business climate	0
Service Survey	Evolution of demand in recent months	0
Service Survey	Evolution of demand expected in the months ahead	0

Note: The table reports the release, the series name and the transformation used. 0 indicates no transformation, 1 indicates quarterly growth rate and 2 indicates monthly growth rate.