CSEF

Centre for Studies in Economics and Finance

WORKING PAPER NO. 240

Nowcasting Euro Area Economic Activity in Real-Time: The Role of Confidence Indicators

Domenico Giannone, Lucrezia Reichlin and Saverio Simonelli

November 2009

University of Naples Federico II | University of Salerno | Bocconi University, Milan

CSEF - Centre for Studies in Economics and Finance – UNIVERSITY OF SALERNO
84084 FISCIANO (SA) - ITALY
Tel. +39 089 96 3167/3168 - Fax +39 089 96 3167 – e-mail: csef@unisa.it

CSEF
Centre for Studies in Economics and Finance

WORKING PAPER NO. 240

Nowcasting Euro Area Economic Activity in Real-Time: The Role of Confidence Indicators

Domenico Giannone[*], Lucrezia Reichlin[**], Saverio Simonelli[***]

Abstract

This paper assesses the role of surveys for the early estimates of GDP in the euro area in a model-based automated procedures 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.

JEL Classification: E52; C33; C53

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

Acknowledgements. Previous versions of this paper have been presented at the workshop on Macroeconomic Forecasting, Analysis and Policy with Data Revision (Montreal, 2006), the 22th Annual Congress of the European Economic Association (Budapest, 2007) and the CSEF seminar series (Napoli, 2008). We thank Marta Banbura, Michele Lenza and Michele Modugno for comments. Saverio Simonelli acknowledges the financial support from the Pierre Werner Chair Programme on Monetary Union (EUI).

[*] ECARES, Université Libre de Bruxelles and CEPR

[**] London Business School and CEPR

[***] University of Naples Federico II, EUI and CSEF. Corresponding address: Department of Economics, University of Naples Federico II - Via Cinthia, 45 - I-80126 Napoli - Italy. E-mail: saverio.simonelli@unina.it

Table of contents

1 Introduction

The world economy has recently suffered the most severe recession in the post war 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 significantly improved. In the euro area these "green shoots" come mostly from qualitative survey data. Survey information is the most timely information on current economic conditions, becoming available before industrial production and GDP. For this reason they are highly watched series by forecasters. However, surveys are not "hard data" since they convey information on sentiments and expectations and might be seriously unreliable.

To understand whether these first 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. 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 designed in Giannone, Reichlin, and Small (2008).

The first objective of this paper is to provide such 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 mix-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 allows to include rich information and retain parsimony.

The rest of the paper is organized as follows. The second Section illustrates methodology and results for the aggregate surveys and, as mentioned, uses GDP forecast for the third quarter of the 2009 as a case study. The third Section describes the model and performs the historical evaluation of the role of disaggregated surveys for the forecast of GDP. The third

Section concludes.

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 data for quarterly growth rate of GDP, 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 the macroeconomic prospects have evolved in the recent months by estimating GDP quarterly growth rate using different vintages of data as they became available each month from April up to September 2009.

Precisely, 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), represents 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 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. At that date, the last available figure for GDP is the -1.5% 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, much below the long term average which is equal to 100.

The release of GDP for the first quarter of 2009 becomes available only with the MoBu of June and it shows a substantial decline, 2.5%, with respect to the previous quarter.

Starting with the MoBu of July, we get some positive signals coming from the economic

[1] Eurostat started producing chained linked GDP measure in 2005. For earlier vintages we use real GDP measured at constat prices.

sentiment indicator: 73 in June from 69 in May. Survey data for July and August, published in the MoBU of August and September respectively, show further improvements.

The improved economic situation is partially confirmed by GDP growth in the second quarter which becomes available with the MoBu of September. In fact, we observe a decline equal to $-.1\%$ which is much less pronounced than what observed for the first quarter. Industrial production is by now available up to June, but this does not 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 interaction 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_{0t} the unobserved monthly growth of GDP and by $M_t = m_{1,t}, ..., m_{k,t}$ a set of monthly predictors. Defining $X_t = (m_{0,t}M_t')'$, the VAR models is the following:

$$X_t = A_1 X_{t-1} + ... + A_p X_{t-p} + u_t \tag{1}$$

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

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

where y_t is observed every third month of the quarter.

If $m_{1,t}, ..., m_{n,t}$ 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 generalization of the bridge equations described in Baffigi, Golinelli, and Parigi (2004); Rünstler and Sédillot (2003); Salazar and Weale (1999). Bridge equations essentially provide a means of relating quarterly data (GDP) to monthly data (typically qualitative 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, generalizes 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 the 2009q3 produced including as 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 were available in each issue of the Monthly Bulletin from April to September. The number of lags p 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 performances of the model evaluated from the first quarter of 2002 onward using real-time database of Giannone, Henry, Lalik, and Modugno (2009) . Under suitable assumptions, these are 68% confidence bands.[3]

Results clearly show that the survey data from July have signaled a substantial improvement for the overall economy. In particular, the point estimates indicate non negative growth in July and in September. In this last month the forecast is also above the average growth experienced over the past five years (0.25 per cent). However, it would be informative to analyze the reliability of these predictions which have been produced using soft data. In order to perform this evaluation, we compare the 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 measure is the same used to define the confidence bands in Figure 2. It is worth stressing that this it is evaluated by looking at the historical accuracy of the forecasts produced by the models in out-of-sample and using

[2] The National Institute of Economic and Social Research, when nowcasting monthly GDP in the UK, use 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] Precisely, we compute the root mean forecast errors of real-time and out-of-sample forecast of GDP growth. For each quarter, the parameters of the model and the forecasts are estimated recursively (out-of-sample) using exclusively the data that were available in the corresponding Monthly Bulletin issue (real-time). For example, uncertainty for September is computed by considering forecast 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 forecast 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.

real-time data as they were available in different issues of the Monthly Bulletin from 2002 onward.

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 relative to the naive benchmark. When we move toward the reference quarter (2009q3) survey 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 survey tend to become more accurate earlier than those obtained with industrial production only. In July, the first month of the third quarter, the forecast based on survey data is as accurate as the forecast that will be produced in October using only industrial production. Further, the last forecast, produced in September, is as accurate as a forecast 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 surveys 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 become available, the advantage of survey based forecast 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 signal that they provide can be considered as a reliable indicator 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 on the ECB Monthly Bulletin are originally collected by the European Commission (Economic and Financial Affairs DG). The series are seasonally adjusted balances of opinion, i.e. constructed as difference between the percentages of respondents giving positive and negative replies. Data are released at the end of the reference month. Precisely, 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; (e) three service confidence indicators (see the appendix for details). Further, for each of these groups, sectorial confidence indicators are computed as simple averages of the indicators in the sector.[5] The economic sentiment indicator is constructed by averaging the sectorial confidence indicators. The industrial confidence indicator has a weight of 40%, the services confidence indicator has a weight of 30%, the consumer confidence indicator has a weight of 20% and the two other indicators have a weight of 5% 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 deal with this problem Giannone, Reichlin, and Small (2008) have proposed to extract common factors from the panel and to regress GDP on them (bridging with factors). The idea consists in considering 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.

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

[4] Industrial capacity utilization 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.

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 on $X_t = (m_{0,t}, M_t', F_t')'$.

In this VAR, we allow for different treatment 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 miss-specification due to weak cross-sectional and serial correlation of the idiosyncratic errors. A similar strategy has been recently adopted by Banbura and Modugno (2009) who allow for arbitrary patterns of missing data. Differently from 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 natural. 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 on euro area data by Angelini, Camba-Méndez, Giannone, Rünstler, and Reichlin (2008) and Banbura and Rünstler (2007).

An alternative approach for exploiting large information consists in averaging many forecasts, each based on a small number of predictors (see Kitchen and Monaco, 2003; Diron, 2006). For the comparison of the two methods (factor models and pooling) and a description of their use for short term forecast 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 polling, i.e. the simple average of the forecasts produced by running many VARs, as described 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 procedures 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, using two alternative estimation strategies, we show that sector-specific information does not provide a significant improvement in the reliability of the predictions.

References

Angelini, E., G. Camba-Méndez, D. Giannone, G. Rünstler, and L. Reichlin (2008): "Short-term forecasts of euro area GDP growth," Working Paper Series 949, European Central Bank.

Baffigi, A., R. Golinelli, and G. Parigi (2004): "Bridge models to forecast the euro area GDP," *International Journal of Forecasting*, 20(3), 447–460.

Banbura, M., and M. Modugno (2009): "Quasi ML estimation of factor model with missing data," Manuscript, European Central Bank.

Banbura, M., and G. Rünstler (2007): "A look into the factor model black box - publication lags and the role of hard and soft data in forecasting GDP," Working Paper Series 751, European Central Bank.

Dempster, A., N. L., and D. Rubin (1977): "Maximum Likelihood Estimation From Incomplete Data," *Journal of the Royal Statistical Society*, 14, 1–38.

Diron, M. (2006): "Short-term forecasts of euro area real GDP growth: an assessment of real-time performance based on vintage data," Working Paper Series 622, European Central Bank.

Doz, C., D. Giannone, and L. Reichlin (2006): "A Maximum Likelihood Approach for Large Approximate Dynamic Factor Models," Working Paper Series 674, European Central Bank.

ECB (2008): "Short-term forecasting in the Euro Area," *Monthly Bulletin*, pp. 69–74.

Giannone, D., J. Henry, M. Lalik, and M. Modugno (2009): "A real time database for the euro area," Ecb, mimeo.

Giannone, D., L. Reichlin, and D. Small (2008): "Nowcasting: The real-time informational content of macroeconomic data," *Journal of Monetary Economics*, 55(4), 665–676.

Kitchen, J., and R. M. Monaco (2003): "Real-Time Forecasting in Practice: The U.S. Treasury Staff Real-Time GDP Forecast System.," *Business Economics*, pp. 10–19.

Mitchell, J., R. J. Smith, M. R. Weale, S. Wright, and E. L. Salazar (2005): "An Indicator of Monthly GDP and an Early Estimate of Quarterly GDP Growth," *Economic Journal*, 115(501), F108–F129.

Rünstler, G., and F. Sédillot (2003): "Short-Term Estimates Of Euro Area Real Gdp By Means Of Monthly Data," Working Paper Series 276, European Central Bank.

Salazar, E., and M. Weale (1999): "Monthly data and short-term forecasting: an assessment of monthly data in a VAR model," *Journal of Forecasting*, 18(7), 447–462.

A Data description

Release	Series	Transformation
Gross Domestic Product	Gross domestic product at constant price	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

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

Table 1: Monthly Bulletin

Monthly Bulletin			Last available data		
Issue	Publication date	Cut-off date	GDP	IP	Survey
April	9-Apr-09	1-Apr-09	08-q4	Jan-09	Mar-09
			(-1.5)	(-3.2)	(64.6)
May	14-May-09	6-May-09	08-q4	Feb-09	Apr-09
			(-1.6)	(-2.2)	(67.2)
June	11-Jun-09	3-Jun-09	09-q1	Mar-09	May-09
			(-2.5)	(-1.6)	(69.3)
July	9-Jul-09	1-Jul-09	09-q1	Apr-09	Jun-09
			(-2.5)	(-1.3)	(73.3)
August	13-Aug-09	5-Aug-09	09-q1	May-09	Jul-09
			(-2.5)	(0.6)	(76.0)
September	10-Sep-09	2-Sep-09	09-q2	Jun-09	Aug-09
			(-0.1)	(-0.5)	(80.6)

The table reports for the 2009 ECB Monthly Bulletins: (i) 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); (ii) 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 the GDP, the month-on-month percentage changes for the Industrial Production and the Economic Sentiment Indicator for the Surveys.

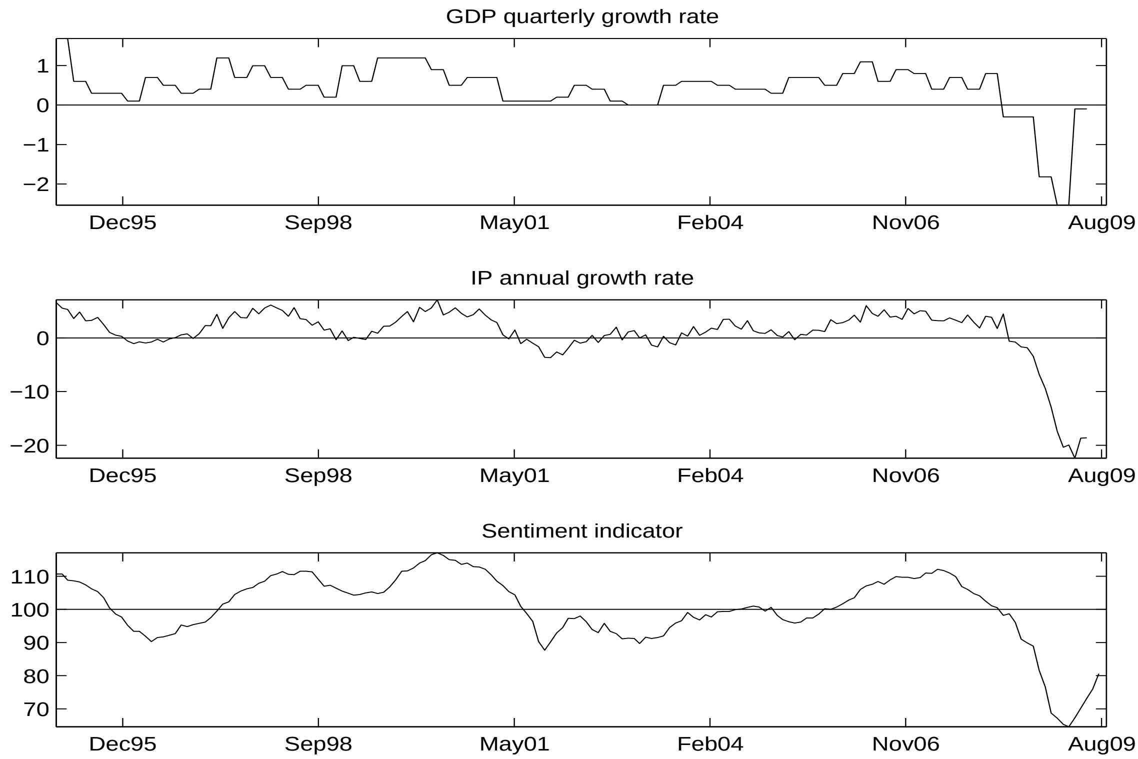

Figure 1: The upper-panel plots the GDP quarter-on-quarter percentage changes; the middle-panel plots the Industrial Production annual growth rate; the bottom-panel plots the Economic Sentiment Indicator for the Surveys.

Table 2: UNCERTAINTY AROUND THE FORECAST OF GDP GROWTH FOR 2009Q3

	Jul-09	Aug-09	Sep-09	Oct-09	Nov-09
RW	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
Stoks 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

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 (columns) and indicate, based on historical performance, how the uncertainty associated with the forecast evolves as information accumulates. RMSFE are computed by performing a real-time and out-of-sample forecasting exercise over the period 2002q1 until 2009q2. The table reports the root-mean-square forecast error (RMSFE) for the Naive model (**RW**), the VAR with GDP, Industrial Producion and each survey at time, the pooling of all the disaggregated VAR (**Pooling**) and the VAR with GDP, Industrial Production and one common factor extracted from all surveys (**Factor**).

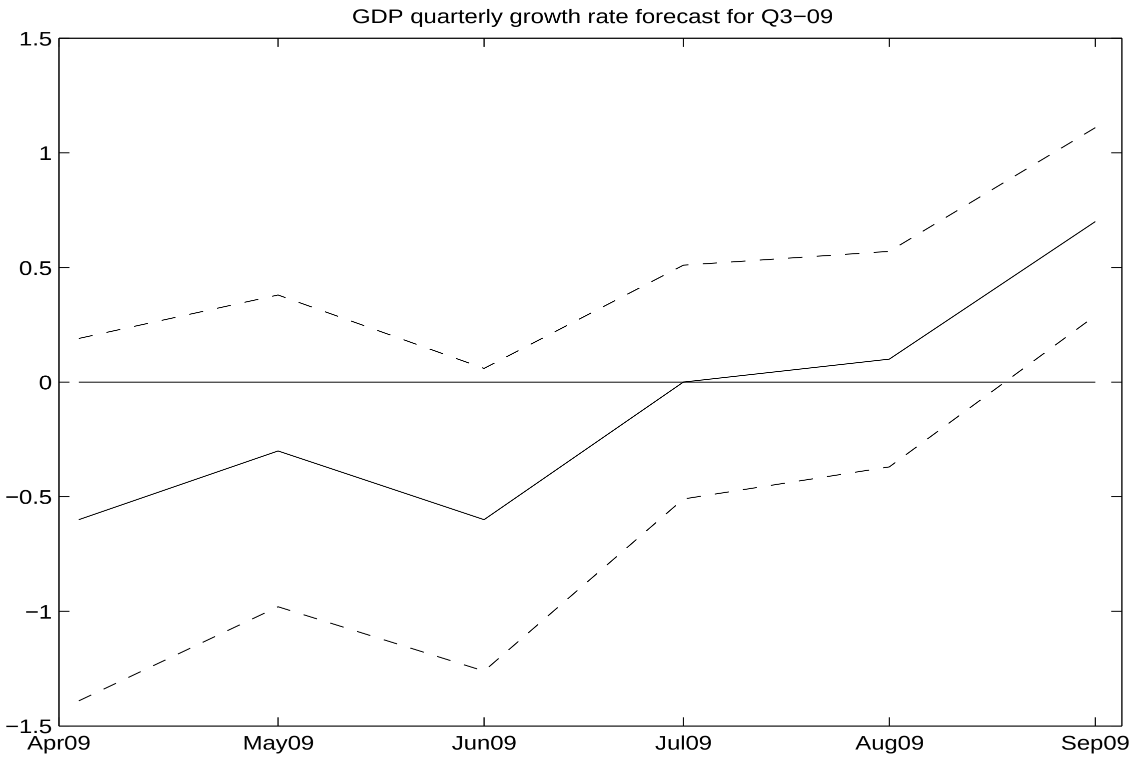

Figure 2: The figure plots the forecast of the GDP quarterly growth rate for Q3-09 (solid line) estimated using the information contained in the monthly Bulletin (x-axis). The forecast is obtained with the VAR model with GDP, Industrial Production and the Economic Sentiment Indicator. Dashed line reports the 68% percent confidence interval based on the historical performances of the model evaluated in out-of-sample and with real time-data from 2002 onward,.

Figure 3: Uncertainty around the forecast of GDP growth for 2009q3

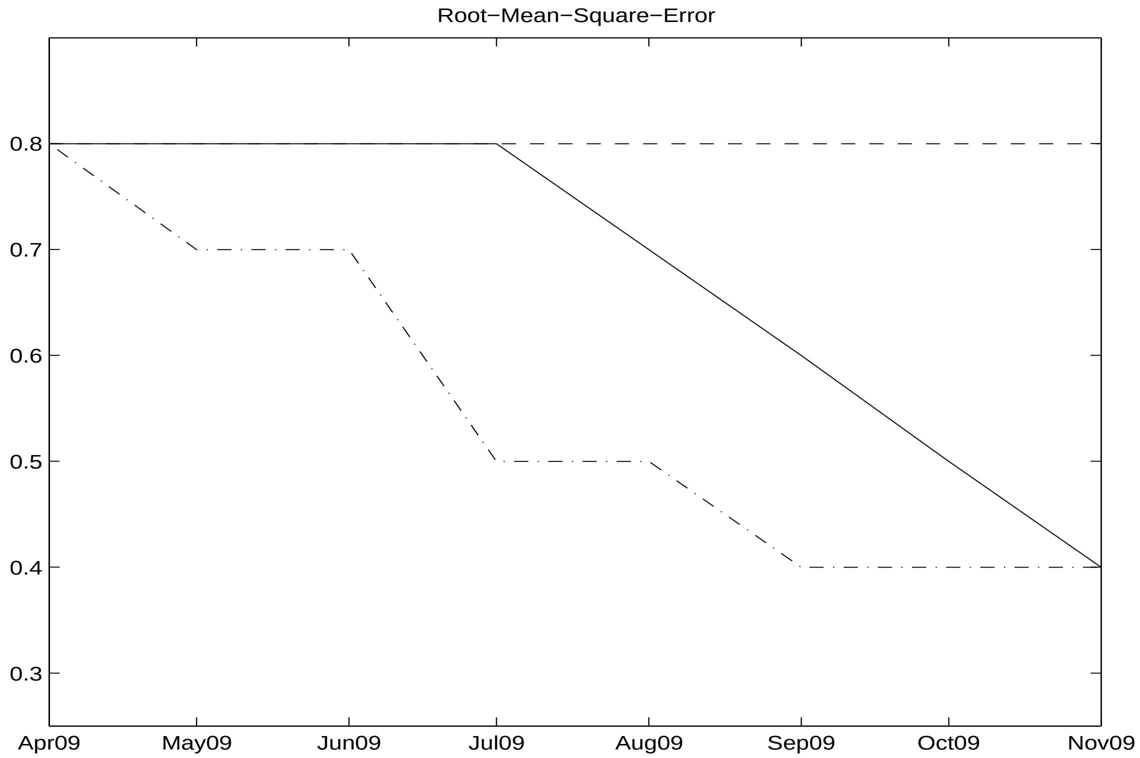

Figure 4: The root-mean-square-forecast-error (RMSFE) estimates for GDP growth are shown as a function of the monthly information contained in the monthly bulletin (x-axis) and indicate, based on historical performance, how we have observed and expect the uncertainty associated with the forecast for 2009q3 shown in Figure 2 to evolve as information accumulates. The figure plots the RMSFE for the Random Walk (dashed line), the VAR with GDP, Industrial Producion and Economic Sentiment Indicator (dashed-doted line) and the VAR with GDP and Industrial Production (solid line). RMSFE are computed by performing a real-time and out-of-sample forecasting exercise over the period 2001q1 until 2009q2.