

E C O N O M I C S B U L L E T I N

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Olivier Darne

University of Paris 10--Nanterre and Banque de France

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Using business survey in industrial and services sector to nowcast GDP growth: The French case*

Olivier DARNÉ[†]

Abstract

This paper proposes new bridge equations for the short-term French GDP forecasting. This tool allows to nowcast the quarterly GDP growth in France for the current quarter, based on the monthly business surveys in the industrial and services sectors. We use an automatic model selection procedure which brings a robust, clear and systematic framework for selecting variables. The forecasting performance for the different selected models is evaluated and we show that taking into account the business surveys in the services sector can be useful for nowcasting GDP growth rate.

Keywords: Short-term analysis; GDP forecasting; bridge equations; business surveys.

JEL Classification: C22; C42; C53.

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[†]Banque de France, and University of Paris X–Nanterre (EconomiX). Email: odarne@u-paris10.fr.

1 Introduction

Policy-makers and analysts are continually assessing the state of the economy. However, gross domestic product [GDP] is only available on quarterly basis with a time span of 2 or 3 months (around 45 days after the end of the reference quarter in France), and sometimes with significant revisions. In this respect, governments and central banks need to have an accurate and timely assessment of GDP growth rate for the current and the next quarters in order to provide a better and earlier understanding of the economic situation.

In this respect, business surveys (soft data) are often used to construct GDP growth indicators (e.g., Grassman and Keereman, 2001; Sédillot and Pain, 2003; Rünstler and Sédillot, 2003; Grenouilleau, 2004), providing timely and reliable pieces of information on business activity. They offer some decisive advantages over hard data: (i) they provide a signal that is obtained directly from the economic leaders regarding the short-term evolution of their activity; (ii) they are published very soon (before the end of the month they relate to), in other words sooner than the main macroeconomic aggregates; (iii) finally, the results are subject to only minor corrections and revisions¹.

Traditionally, analysts used to favor the results from the business survey in industry. Two main reasons are proposed. Firstly, analysts are above all concerned about the contribution to the global growth of the economy; the industrial activity only represents 27% of the value added (VA) - which is less than the services sector's share in the VA - however, it contributes up to 36% to the variance of the value added. Secondly, historically, more data are available in the industrial sector and with a longer time span. However, in France, as in the other developed economies, the services sector tends to play an increasing role: (i) this sector represents 40% of the whole value added; (ii) it explains about 25% of the value added variance; (iii) from 1980 to 2004, the percentage of service activities in the employment of the competitive sector increased by 15 points, from 20% to 35%, in line with the outsourcing of some jobs in the industry and the recent growth of temporary work. Therefore, having an accurate insight of the services sectors seems crucial to better understand the overall economic outlook. In this respect, the services business survey conducted by Banque de France plays a key role, as it yields the first available data.

Banque de France [BdF] has a forecasting tool² for the quarterly GDP growth in

¹Banbura and Rünstler (2007) find that real activity data (hard data) are the most important source of information. However, they show, once their publication lag is taken into account, real activity data are much less relevant, while surveys take their place.

²This tool, the Monthly Index of Business Activity (MIBA), is published by Banque de France every

France for the current quarter and for the next quarter, based on the monthly business surveys in the industrial sector published in Monthly Business Survey (MBS) of BdF. This tool provides three monthly forecasting exercises of GDP growth rate for a given quarter. The aim of this paper is to introduce the services business survey in the GDP modelling in order to improve the forecasting accuracy.

2 The BdF business survey

BdF has carried out a monthly business survey in industry in January 1987. The field investigated covers agriculture and agri-food industry, consumer goods, automotive industry, capital goods, and intermediate goods. A business survey in the services sector was carried out in January 1989 and covers the following fields: business services, hotels, haulage activities and automotive repairs. Initially, the services survey was bimonthly. Since June 2002, the survey results are published on a monthly basis. In order to obtain data in services sector with a long time span, the series have been interpolated using the skipping approach proposed by Gómez and Maravall (1994)³.

We take into account fourteen and seven main balances of opinions of the industry and services surveys, respectively. Note that the answers refer to the economic situation on the previous month⁴.

3 Monthly exercises

The model is designed to be used on a monthly basis, and we provide three forecasts for the current quarter or nowcasts of the GDP growth rate. As soon as information is available (around the beginning of the second month of the quarter), the first estimate of the growth rate for the current quarter will be computed, then one month later the second and two months later the third and last estimate. Thus, the three estimates will be computed around 90, 60 and 30 days, respectively, before the official release of GDP figures by Insee (the French national statistics institute). For the last estimate we have the three monthly values of the quarter of interest from business survey. When data are missing for some months of this quarter, the value for the quarter is computed

month.

³See Marcellino (1998) for survey on interpolation data.

⁴In European Commission surveys, answers refer to the economic situation over the recent period (usually 3 months) including the current month.

as the 3-month moving average of the last available observations⁵.

For short-term forecasting of the French GDP growth, we construct bridge models (BM, henceforth). These linear regressions "bridge" (i.e. link) monthly variables and quarterly GDP growth. Such models have been widely considered in the literature especially to forecast GDP growth in national and international institutions (Grassman and Keereman, 2001; Sédillot and Pain, 2003; Rünstler and Sédillot, 2003; Baffigi et al., 2004; Diron, 2006).

The BM relates quarterly average of the monthly explanatory variables (X_t) to quarterly GDP growth (Y_t). The general specification of the autoregressive-distributed-lag (ADL) bridge model is as follows

$$Y_t = \alpha + \sum_{i=1}^m \beta_i Y_{t-i} + \sum_{j=1}^q \sum_{i=0}^k \delta_{j,i} X_{j,t-i} + \varepsilon_t$$

where X_t 's represent the factors obtained from principal component analysis for the business survey in industry and services sectors. We retain four factors ($k = 4$) and we set $m = q = 4$.

BMs are specified by using a general-to-specific (Gets) approach implemented in an automated way by Hoover and Perez (1999) and improved by Krolzig and Hendry (2001), which allows exploiting the availability of a large number of time series. These BMs are estimated using quarterly averages of monthly data as explanatory variables.

In this study, we use GRO CER⁶ (Dubois, 2003), a computer program which implements the Gets modelling. This automatic model selection procedure has four basic stages in its approach to select a parsimonious undominated representation of an overly general initial model, denoted the general unrestricted model (GUM) containing all variables likely (or specified) to be relevant, including the maximum lag length of the independent and dependent variables: (i) estimation and testing of the GUM; (ii) a pre-search process to remove insignificant variables in the GUM; (iii) a multipath search procedure which checks the validity of each reduction until terminal selections using diagnosis - these terminal models are tested against their union until a unique undominated congruent model is selected; and (iv) a post-search evaluation to check the reliability of the selection using overlapping sub-samples (see Hendry and Krolzig,

⁵We also computed the missing values from an AR model, and we obtained the same forecasting results than with the 3-month moving average.

⁶GRO CER is an open source econometric toolbox for the software Scilab (Dubois, 2003). For more information, refer to <http://dubois.ensae.net/grocer.html>. Krolzig and Hendry (2001) implemented Gets modelling in the computer program PcGets.

2001).

The search for variables to be included in the BMs is guided by timeliness, stability and parsimony. The models should also contain a limited number of variables to prevent overspecification and to facilitate updates once the models are operative. We propose three BMs: (1) BMINDU only based on business survey in industry, (2) BMSERV only based on business survey in services sector, and (3) BMINSV based on business survey in industry and services sectors.

We estimate the bridge models by OLS with robust standard error calculations over the period from 1989Q1 to 2007Q4. Various residual diagnostic tests reveal no discernible specification errors.

4 Forecasting

Out-of-sample rolling forecasts are carried out to evaluate the BMs. The rolling forecasts have been implemented over the period 2003Q1-2007Q4, with three forecasts by quarter. This exercise takes into account the availability of data, under the assumption that a forecasting exercise will be implemented at each beginning of month.

For each quarter t , we provide with three forecasts for the current quarter (or nowcasts), \hat{Y}_t^i , for $i = 1, 2, 3$. The root mean-squared error (RMSE) for the i^{th} forecast is defined as

$$\text{RMSE}(i) = \sqrt{\frac{1}{n} \sum_{t=1}^n (Y_t - \hat{Y}_t^i)^2},$$

where n is the number of quarters considered in the rolling forecast exercise ($n = 20$ from 2003Q1 to 2007Q4).

Benchmark results correspond to AR model and to naive projections. Forecasts with the AR model present the following form, for all t

$$\hat{Y}_t = \hat{\phi}_0 + \sum_{i=1}^4 \hat{\phi}_i Y_{t-i}$$

The naive projections are estimated by taking the last observation as the forecast, that is for all t

$$\hat{Y}_t = Y_{t-1}$$

For the two benchmark approaches, there is a single forecast by quarter as we do not include any monthly information. Results in terms of RMSE are presented in Table 1.

For all BMs, the RMSEs are lower than those of the benchmark models. It is also noteworthy that AR forecasts (0.326) are always more accurate than naive projections (0.463), meaning that information is present inside data taking the form of non-null autocorrelations. Furthermore, as expected, the accuracy of projections generally increases with each forecast: in most cases, the smallest RMSEs are observed for the third forecast. Thus, the performance of the BMs is improved when growing the availability of some information on the current quarter.

Moreover, the RMSEs from the three BMs are very close for the first and second nowcasts but the BMINDU and BMINSV models give the smallest RMSEs (0.246 and 0.240, respectively) than the BMSERV model for the third nowcast (0.268). Therefore, the business surveys in the services sector can be useful for nowcasting the GDP growth rate.

Diebold-Mariano tests of equality of forecast performance are carried out (Table 2)⁷. The DM tests indicate that the forecasts of the three BMs significantly outperform benchmark AR forecasts. We find that the forecasts from the BMs are not significantly different, suggesting that the business surveys in the services sector can be another valuable source of information for short-term analysis.

Table 1: RMSEs for the BMs for the first, second and third forecasts and for the AR and naive models, over the period 2003Q1–2007Q4.

Model	First	Second	Third	AR	Naive
BMINDU	0.294	0.275	0.246	0.326	0.463
BMSERV	0.284	0.269	0.268		
BMINSV	0.303	0.272	0.240		

5 Conclusion

In this paper, bridge equations for French GDP growth based on monthly business survey in industrial and services sectors for the current quarter have been presented. We showed that taking into account the business surveys in the services sector can be useful for nowcasting the GDP growth rate.

⁷We also applied the modified Diebold-Mariano tests of Harvey et al. (1997) to take into account the relatively short number of forecasts but the results obtained are the same.

Table 2: Diebold-Mariano tests over the period 2003Q1–2007Q4.

Model	First	Second	Third	Naive
<i>Model AR as benchmark</i>				
BMINDU	2.78*	4.13*	3.41*	-5.43*
BMSERV	3.42*	4.02*	4.13*	
BMINSV	2.13*	5.12*	2.73*	
<i>Model BMINDU as benchmark</i>				
BMSERV	0.78	-1.44	-1.63	
BMINSV	-0.92	0.47	-0.59	

* Significant at the 5% level. If $DM > 1.96$ then the tested model is better than the benchmark model.

If $DM < -1.96$ then the benchmark model is better than the tested model.

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