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Financial variables as leading indicators of GDP growth: Evidence from a MIDAS approach during the Great Recession

Laurent Ferrara
Clément Marsilli

UMR 7235

Université de Paris Ouest Nanterre La Défense
(bâtiment G)
200, Avenue de la République
92001 NANTERRE CEDEX

Tél et Fax : 33.(0)1.40.97.59.07
Email : nasam.zaroualete@u-paris10.fr

Financial variables as leading indicators of GDP growth: Evidence from a MIDAS approach during the Great Recession

Laurent Ferrara* Clément Marsilli†

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Abstract

The global economic recession, referred to as the *Great Recession*, endured by the main industrialized countries during the period 2008-09, in the wake of the financial and banking crisis, has pointed out the current importance of the financial sector in macroeconomics. In this paper, we evaluate the predictive power of some major financial variables to anticipate GDP growth in euro area countries during this specific period of time. In this respect, we implement a MIDAS-based modeling approach, put forward by Ghysels *et al.* (2007), that enables to forecast quarterly GDP growth rates using exogenous variables sampled at higher frequencies. Empirical results show that, overall, stock prices help to improve the accuracy of GDP forecasts by comparison with a standard opinion survey variable, while oil prices and term spread appear to be less informative.

JEL Classification:
C2, C5, E3.
Keywords:
Great Recession, Forecasting, Financial variables, MIDAS approach.

*Banque de France, International Macroeconomics Division, and EconomiX, UMR CNRS 7235, University Paris Ouest Nanterre La Défense, laurent.ferrara@banque-france.fr

†Banque de France, International Macroeconomics Division, and University Franche-Comté, clement.marsilli@banque-france.fr. The views expressed herein are those of the authors and do not necessarily reflect those of the Banque de France.

1 Introduction

In the wake of the financial and banking crisis, most of all industrialized countries have experienced a very severe economic recession during the years 2008 and 2009, sometimes referred to as the Great Recession.

This Great Recession has emphasized the necessary re-assessment of financial markets in their ability to anticipate the business cycle. Regarding the role of financial market variables, there is a huge literature pointing out the leading property of those series to forecast macroeconomic fluctuations (see a review in Stock and Watson, 2003). For example, Kilian, 2008, reviewed the impact of energy prices shocks, especially oil prices, on macroeconomic fluctuations and Hamilton, 2003, put forward a non-linear Markov-Switching model to predict US GDP growth rate through oil prices. The term spread has also been widely considered in empirical approaches to assess in a quantitative manner future GDP growth, we refer among others to Estrella et al. (2003) for the US and to Duarte et al. (2005) or Bellégo and Ferrara (2009) for the euro area. Recently, Farmer (2011) also emphasized the major role of stock prices during the recent Great Recession.

When dealing with variables sampled at various frequencies (quarterly GDP and monthly financial information), the MIDAS approach put forward by Ghysels and his co-authors has proved to be a useful tool (see Ghysels et al., 2007). Especially in the forecasting framework, several empirical papers have shown the ability of financial information to predict macroeconomic fluctuations; we refer for example to Clements and Galvao (2008) for the US or Marcellino and Schumacher (2010) for Germany.

In this paper, we assess the impact of financial returns as leading indicators for GDP growth for the four main euro area countries (Germany, France, Italy and Spain), as well as for the euro area as a whole. We carry out a forecasting analysis, over the period ranging from 2007q1 to 2009q4, focused on three well-known financial variables, namely oil prices, stock prices, and spread between long and short interest rates, for several forecasting horizons.

2 The MIDAS framework

The MIDAS approach (MIxed DAta Sampling) has been put forward in the econometric literature by Ghysels and his co-authors (see Ghysels *et al.*, 2007) and enables to use variables of various frequencies in a single univariate model. Especially a MIDAS regression allows to explain a low frequency variables by exogenous variables of higher frequency, without any aggregation procedure and within a parsimonious framework.

This approach is typically used in macroeconomics to describe quarterly GDP fluctuations using monthly data that are generally available for short-term analysts, as for example industrial production index, retail sales, housing permits or opinion surveys.

The standard univariate MIDAS regression for explaining a stationary variable (y_t), augmented with a first order autoregressive component, is given by:

$$y_t = \beta_0 + \beta_1 \ B(\theta) \ x_t^{(m)} + \lambda y_{t-1} + \varepsilon_t \tag{1}$$

where $(x_t^{(m)})$ is an exogeneous stationary variable sampled at a frequency higher than (y_t) such that we observe m times $(x_t^{(m)})$ over the period $[t-1, t]$. The term $B(\theta)$ controls the polynomial weights that allows the frequency mixing. Indeed, the MIDAS specification consists in smoothing the past values of $(x_t^{(m)})$ by using the polynomial $B(\theta)$ of the form,

$$B(\theta) = \sum_{k=1}^{K} b_k(\theta) L^{(k-1)/m} \tag{2}$$

where K is the number of data points on which the regression is based, L is the lag operator such that $L^{s/m} x_t^{(m)} = x_{t-s/m}^{(m)}$, and b_K is the weight function that can take various shapes. As in Ghysels et al. (2007), we implement the two parameter exponential Almon lag polynomial such as $\theta = (\theta_1, \theta_2)$,

$$b_k(\theta) \equiv b_k(\theta_1, \theta_2) = \frac{\exp\left(\theta_1 k + \theta_2 k^2\right)}{\sum_{k=1}^{K} \exp\left(\theta_1 k + \theta_2 k^2\right)} \tag{3}$$

The parameter θ is part of the estimation problem. It is only influenced by the information conveyed by the last K values of the high frequency variable $(x_t^{(m)})$; the windows size K being an exogenous specification. Other parameterizations of the weight functions have been used in the literature, but we choose (3) since it constitutes a parsimonious and reasonable restriction for which the weights are always positive.

In our work, we use univariate MIDAS regressions designed to accommodate direct multi-step forecasting such that:

$$y_{t+h|t} = \hat{\beta}_0^{(h)} + \hat{\beta}_1^{(h)} \ B\left(\hat{\theta}^{(h)}\right) \ x_t^{(m)} + \hat{\lambda}^{(h)} \, y_t \tag{4}$$

where h is the monthly forecast horizon, (y_t) is the quarterly GDP growth, and $(x_t^{(m)})$ is the monthly financial return. Within this framework, we get that $m = 3$.

3 Empirical Results

In this section, we implement forecasts for quarterly GDP growth rates for each of the main euro area countries (Germany, France, Italy and Spain), as well as for the euro area as a whole, starting from the same set of explanatory variables, namely oil prices, stock prices and the spread between long and short-term interest rates (10-year government bond - 3-month interbank rate). The financial time series are detailed in Table 1.

The output growth measure considered in this study is the quarterly growth rate of chain-linked Gross Domestic Product as released by the national instituts of statistics of the four countries, namely: INSEE (France) , DeStatis (Germany), Istat (Italy), and INE (Spain) and by Eurostat for the euro area at mid-July 2011.

	Description	Transformation
Real output		
GDP	GDP growth in France, Germany, Italy, Spain, and euro area (resp. INSEE, DeStatis, Istat, INE, Eurostat)	Quarterly growth rate
Financial covariates		
Stocks	CAC40, DAX, FTSE MIB, IBEX35, and DJ Eurostoxx50 indices (Bloomberg)	Monthly log-return
Oil	Oil price quoted at New York Mercantile Exchange (Bloomberg)	Monthly log-return
Spread	Term spread: 10 years Government bond - 3 months interbank rate (Euribor 3m) (National Central Banks and European Central Bank)	Monthly Δ
Benchmark		
ESI	*Economic Sentiment Indicator* in France, Germany, Italy, Spain, and euro area (Eurostat)	Monthly Δ

Table 1: Description of variables

We carry out an in-sample analysis over the period 1990q1-2006q4, then we implement a quasi-real-time experience over the crisis period from 2007q1 to 2009q4. Knowing that financial data are available the last working day of the month, we suppose that forecasts for a given quarter are computed at the end of each month, for 12 horizons ranging from $h = 0$ (nowcasts computed at the end of the last month of the reference quarter) to $h = 11/3$ (forecasts computed 11 months before the end of the reference quarter). For each date t, the MIDAS regression optimally exploits the monthly fluctuations of the last $K = 10$ data of the $(x_t^{(m)})$ series using the weight polynomial, given in equation (2).

In this paper, for each of the five economies (France, Germany, Italy, Spain, and euro area), we specify three univariate MIDAS regressions based on the three financial variable returns. The direct multi-step forecasting approach used in our work allows parameter estimation using an OLS method and unconstrained Levenberg-Marquardt algorithm on Matlab, for each horizon from $h = 0$ to $h = 11/3$.

In order to evaluate the accuracy of those forecasts, we compare them with those stemming from a benchmark MIDAS model based on the Economic Sentiment Index as leading indicator (noted *ESI MIDAS*), a key opinion survey variable to predict output growth, see for example Mourougane and Roma (2003) or Ferrara (2007)[1]. As a comparative measure, we present in table 2 the ratios of Root Mean Squared Forecasting Errors (RMSFEs) of GDP growth between the *Financial MIDAS* models and the benchmark *ESI MIDAS* model for each h horizon defined by:

$$r^{(h)} = \frac{\text{RMSFE}^{(h)}_{\text{Financial MIDAS}}}{\text{RMSFE}^{(h)}_{\text{ESI MIDAS}}}$$

For a given horizon h, when the ratio $r^{(h)}$ is lower than one, it means that the MIDAS model based on a given financial variable outperforms the benchmark *ESI MIDAS* model and the opposite prevails when the ratio is greater than one (see results in table 2).

	Forecasting horizons h											
	0	1/3	2/3	1	4/3	5/3	2	7/3	8/3	3	10/3	11/3
France												
Stocks	1,04	1,02	0,95	1,05	0,85	0,91	1,00	0,97	0,99	0,97	0,94	1,01
Oil	0,96	0,94	1,22	1,14	1,05	1,20	1,05	1,03	1,09	1,06	1,02	1,03
Spread	1,12	1,04	1,27	1,15	1,03	1,17	1,03	0,98	1,06	1,04	1,00	1,01
Germany												
Stocks	1,23	1,23	1,09	1,11	0,97	1,06	1,02	1,01	1,01	0,97	0,98	1,01
Oil	1,21	1,19	1,18	1,24	0,99	0,97	1,01	1,03	1,05	1,01	0,98	1,03
Spread	1,17	1,20	1,20	1,23	1,13	1,06	1,02	1,00	1,02	1,00	1,00	1,03
Italy												
Stocks	0,92	0,92	1,02	1,05	0,87	1,01	1,05	1,06	1,07	1,11	1,04	1,04
Oil	0,95	0,95	1,19	1,23	1,02	1,15	1,09	1,18	1,17	1,24	1,14	1,09
Spread	1,00	0,95	1,13	1,23	1,02	1,12	1,12	1,11	1,15	1,19	1,08	1,06
Spain												
Stocks	1,33	1,46	0,96	1,00	0,94	1,11	1,13	1,14	1,18	1,21	1,21	1,33
Oil	1,44	1,41	0,87	0,93	0,87	1,17	1,25	1,26	1,21	1,23	1,23	1,36
Spread	1,38	1,36	0,94	1,14	1,04	1,24	1,25	1,22	1,26	1,28	1,29	1,45
Euro Area												
Stocks	0,91	0,87	1,03	1,05	0,95	0,98	0,98	0,97	0,98	0,97	0,96	0,98
Oil	1,00	0,96	1,21	1,19	1,10	1,06	1,05	1,05	1,11	1,04	1,02	1,02
Spread	1,02	0,99	1,20	1,18	1,11	1,11	1,09	1,02	1,11	1,06	0,98	1,03

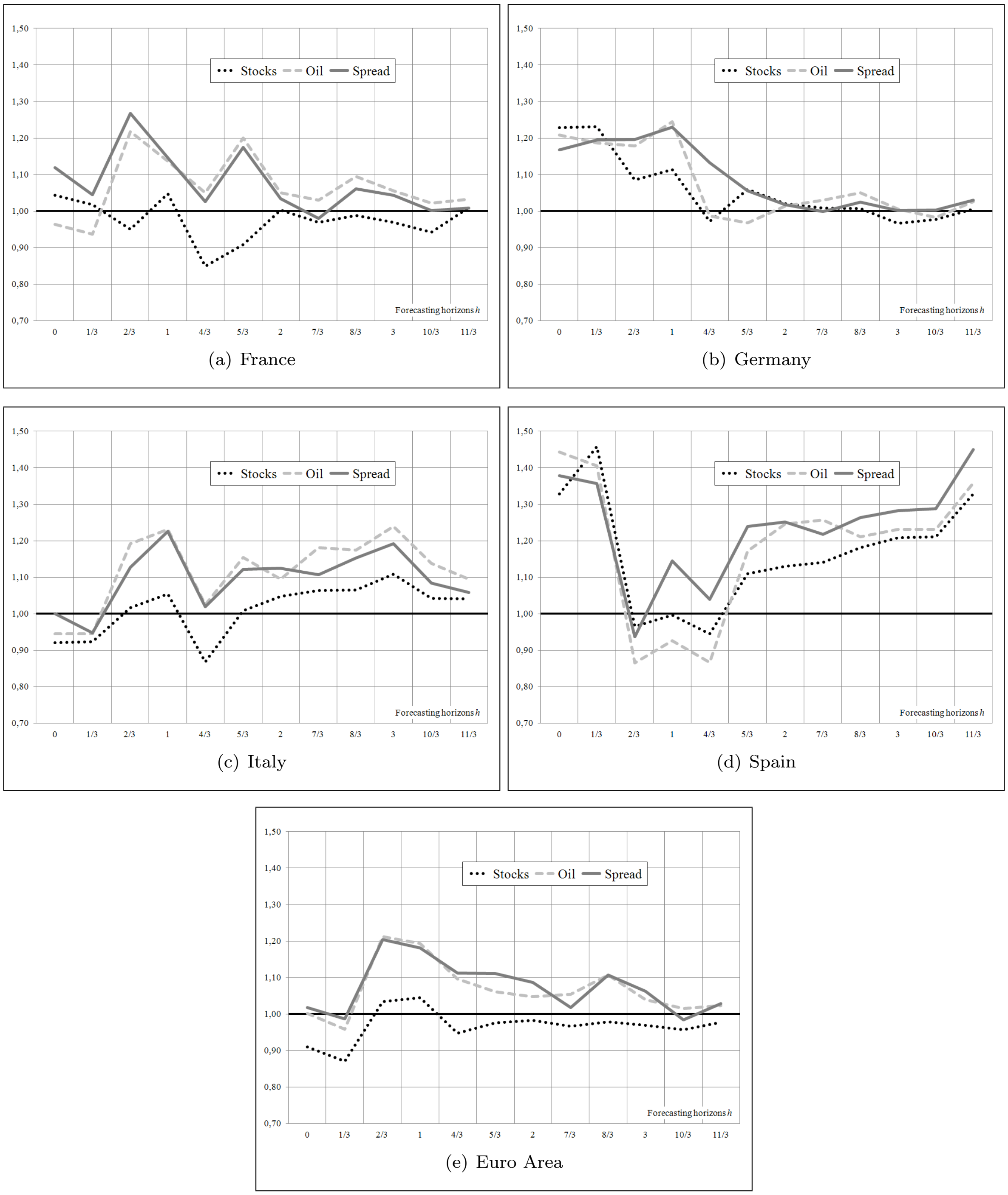
Table 2: Ratio $r^{(h)}$ of RMSFE for the five economies and the three financial variables

Starting from the results presented in table 2 and figure 1, we can draw below some conclusions that seem useful for practitioners.

First, for all five economies, it turns out that financial MIDAS models are able to improve the benchmark ESI MIDAS model for at least one forecasting horizon, although the gain is not uniform through various horizons. In general, the optimal forecast horizon lies between 3 and 5 months, depending on the country: over 4 months for Italy, from 4 to 5 months for Germany and France, and 2 to 4

[1] Obviously, note that empirical results are conditioned by this choice.

months for Spain. This horizon is often encountered as the optimal horizon for financial variables in the empirical literature that deals with the linkages between financial and macroeconomic variables. When comparing financial variables according to their forecasting power, it turns out that stock prices generally seem to be the most informative variable in terms of predicting output growth, specially for France, Italy, and the Euro Area. In fact, this Great Recession was initiated by a turmoil on financial markets, equity prices having experienced large falls. Thus this does not seem surprising that stock



(a) France (b) Germany (c) Italy (d) Spain (e) Euro Area

Figure 1: Evolution of RMSFE ratios $r^{(h)}$ according h, for the five economies and the three financial variables

prices possess a predictive power over macroeconomic evolutions from 2007 to 2009. In opposition, the term spread does not clearly improve forecasting results from the ESI, for all five economic areas. It turns out that this variable is a reliable predictor of turning points in the business cycles, as advocated in many papers (see for example Rubebusch and Williams, 2009), but does not appear as precise predictor of quantitative GDP growth. The same remark holds for oil prices. Indeed, in general, oil prices do not help to improve forecasts by comparison with the ESI, except in the case of Spain for which the oil price variable gives significant better results than the ones obtained from ESI, for forecast horizons ranging from 2 to 4 months (ratios lower than 0.90). Note also that oil prices present a ratio lower than one for Italy and France, for a very short term horizon (the last two months).

Lastly, when comparing countries, it turns out that for France, stock prices provide significantly better results in forecasting GDP than the ESI, for almost each forecast horizon, which is a remarkable result. Also for the Euro Area as a whole, stock prices lead to an almost systematic gain by comparison with the ESI, except for the 2-month and 3-month horizons. As regards other countries, it is striking to note that those financial variables do not help to improve German GDP forecasts by comparison with the ESI. This result is interesting for practitioners in charge of short-term forecasting for Germany. This means that variables reflecting macroeconomic fundamentals, like for example industrial production index, are likely much more important to get accurate macroeconomic forecasts than financial market variables. For Spain, only oil prices possess a leading pattern between 2 and 4 months. For Italy, we observe a gain as regards stock prices for $h = 0, 1$ and also the ratio is lower than 0.90 for $h = 4$.

4 Conclusions

In this paper, we compare the forecasting ability of three well known financial variables (oil prices, stock prices and term spread), through a MIDAS approach, with a synthetic opinion survey (the European Sentiment Indicator), for various euro area GDPs (Germany, France, Italy, Spain and the euro area as a whole). Indeed, financial and soft data are often used by short-term forecasters due to their timeliness and leading properties, by comparison with hard data such as industrial production. From the results that we get, it turns out that stock prices generally enable to improve forecasting accuracy by comparison with the soft indicator, while term spread and oil prices do not help in general. In addition, we show that for Germany financial variables do not present a better predictive power than soft data, while results are mixed for other countries and strongly depend on the forecast horizon.

References

[1] Bellégo, C. and Ferrara, L. (2009), Forecasting Euro Area recessions using time-varying binary response models for financial variables, Working Paper, Banque de France, No. 259

[2] Clements, M. and Galvao, A.-B. (2008), Macroeconomic forecasting with mixed-frequency data : forecasting output growth in the United States, *Journal of Business and Economic Statistics*, 26.

[3] Duarte, A., Venetis, I.A., and Paya, I. (2005), Predicting real growth and the probability of recession in the Euro-area using the yield spread, *International Journal of Forecasting*, 21, 2, 261-277.

[4] Estrella, A., Rodrigues, A. P., and Schich, S. (2003), How stable is the predictive power of the yield curve? Evidence from Germany and the United States, *Review of Economics and Statistics*, 85, 3, 629-644.

[5] Farmer, R. (2011), The stock market crash of 2008 caused the Great Recession: Theory and evidence, Working Paper No.17479, NBER, October 2011.

[6] Ferrara, L. (2007), Point and interval nowcasts of the Euro area IPI, *Applied Economics Letters*, 14,2, 115-120.

[7] Ghysels, E., Sinko, A. and Valkanov, R. (2007), MIDAS regressions: further results and new directions, *Econometic Reviews*, 26, 53-90.

[8] Hamilton, J. (2003), What is an oil shock?, *Journal of Econometrics*, 113, 363-398.

[9] Kilian, L. (2008), The economic effects of energy price shocks, *Journal of Economic Literature*, 46, 871-909.

[10] Marcellino, M. and Schumacher, C. (2010), Factor-MIDAS for now- and forecasting with ragged-edge data: a model comparisaon for German GDP, *Oxford Bulletin of Economics and Statistics*, 72, 4, 518-550.

[11] Mourougane, A. and Roma, M. (2003), Can confidence indicators be useful to predict short term real GDP growth, *Applied Economics Letters*, 10, 8, 519-522.

[12] Rudebusch G. and Williams J. (2009), Forecasting recessions: The puzzle of the enduring power of the yield curve, *Journal of Business and Economics Statistics*, 27, 4, 492-503.

[13] Stock, J.H. and M.W. Watson (2003), Forecasting output and inflation: the role of asset prices, *Journal of Economic Literature*, 41, 3, 788-829.