DOCUMENT

DE TRAVAIL

N° 454

FORECASTING GROWTH DURING THE GREAT RECESSION:

IS FINANCIAL VOLATILITY THE MISSING INGREDIENT?

Laurent Ferrara, Clément Marsilli and Juan-Pablo Ortega

October 2013

BANQUE DE FRANCE

EUROSYSTÈME

DIRECTION GÉNÉRALE DES ÉTUDES ET DES RELATIONS INTERNATIONALES

DIRECTION GÉNÉRALE DES ÉTUDES ET DES RELATIONS INTERNATIONALES

FORECASTING GROWTH DURING THE GREAT RECESSION:

IS FINANCIAL VOLATILITY THE MISSING INGREDIENT?

Laurent Ferrara, Clément Marsilli and Juan-Pablo Ortega

October 2013

Forecasting growth during the Great Recession: is financial volatility the missing ingredient?

Laurent Ferrara[1] – Clément Marsilli[2] – Juan-Pablo Ortega[3]

[1]Banque de France, International Macroeconomics Division. laurent.ferrara@banque-france.fr
[2]Banque de France, International Macroeconomics Division and Laboratoire de Mathématiques de Besançon, Université de Franche-Comté. Corresponding author: clement.marsilli@banque-france.fr.
[3]Centre National de la Recherche Scientifique, Laboratoire de Mathématiques de Besançon, Université de Franche-Comté. juan-pablo.ortega@univ-fcomte.fr
We would like to thank Valérie Mignon, Olivier Darné, and two anonymous referees for their helpful comments and suggestions. The views expressed herein are solely those of the authors and do not necessarily reflect those of the Banque de France.

Résumé

La récente "Grande Récession" subie par la majeure partie des pays industrialisés pendant la période 2008-2009, dans le sillage de la crise financière mondiale, a souligné le rôle prépondérant du secteur financier dans les fluctuations macroéconomiques. De nombreux travaux de recherche ont, dès lors, reconsidéré les liens existants entre les sphères financière et réelle. Dans cet article, nous évaluons le contenu prédictif de la volatilité des variables financières, en focalisant sur le prix des matières premières et le cours des actions. Dans cette optique, nous mettons en place une extension d'un modèle de type MIDAS (*Mixed Data Sampling*) qui permet la prévision du taux de croissance trimestriel du Produit Intérieur Brut à l'aide de variables échantillonnées à des fréquences plus élevées. Les résultats empiriques sur trois pays industrialisés (États-Unis, France et Royaume-Uni) montrent qu'un modèle incluant volatilités financières journalières et indice de production industrielle mensuel se serait révélé particulièrement adapté à la prévision de la croissance du PIB lors de la "Grande Récession".

Mots-Clés – Grande Récession, Prévision du PIB, Variables financières, Approche MIDAS, Volatilité.

Codes JEL – C53, E17

Abstract

The Great Recession endured by the main industrialized countries during the period 2008-2009, in the wake of the financial and banking crisis, has pointed out the major role of the financial sector on macroeconomic fluctuations. In this respect, many researchers have started to reconsider the linkages between financial and macroeconomic areas. In this paper, we evaluate the leading role of the daily volatility of two major financial variables, namely commodity and stock prices, in their ability to anticipate the output growth. For this purpose, we propose an extended MIDAS (Mixed Data Sampling) model that allows quarterly output growth rate forecasting using exogenous variables sampled at various higher frequencies. Empirical results on three industrialized countries (US, France, and UK) show that mixing daily financial volatilities and monthly industrial production is useful at the time of predicting gross domestic product growth over the Great Recession period.

Keywords – Great Recession, Forecasting, Financial variables, MIDAS approach, Volatility.

JEL classification – C53, E17

Introduction

In the wake of the financial and banking crisis, virtually all industrialized countries experienced a very severe economic recession during the years 2008 and 2009, generally referred to as the Great Recession. This recession has shed light on the necessary re-assessment of the contribution of financial markets to the economic cycles. There is a huge volume of work in the literature that underlines the leading role of financial variables in the forecasting of macroeconomic fluctuations. For example, Kilian (2008) reviewed the impact of energy prices shocks, especially oil prices, on macroeconomic fluctuations; Hamilton (2003) put forward a non-linear Markov-Switching model to predict the US Gross Domestic Product (GDP) growth rate using oil prices. Stock and Watson (2003) have proposed a review on the role of asset prices for predicting the GDP, while Claessens et al. (2012) have empirically assessed interactions between financial and business cycles. Recently, Bellégo and Ferrara (2012) have proposed a factor-augmented probit model enabling to summarize financial market information into few synthetic factors in order to anticipate euro area business cycles.

Nevertheless, there are only very few studies in the literature dealing with the impact of financial volatility on macroeconomic fluctuations. Among the rare existing references, Hamilton and Lin (1996) have shown evidence of relationships between stock market volatility and US industrial production through non-linear Markov-Switching modeling; Ahn and Lee (2006) have estimated bi-variate VAR models with GARCH errors for both industrial production and stock indices in five industrialized countries. Chauvet et al. (2012) have recently analyzed the predictive ability of stock and bond volatilities over the Great Recession using a monthly aggregated factor. Indeed, they estimate a monthly volatility common factor based on realized volatility measures for stock and bond markets. They show that this volatility factor largely explains macroeconomic variable during the 2007-2009 recession, both in-sample and out-of-sample.

When dealing simultaneously with daily financial variables and quarterly macroeconomic variables, a standard way to proceed is to temporally aggregate the high frequency variable in order to assess dependence at the same frequency between both types of variables; this approach inevitably leads to a loss of information that can compromise the forecasting efficiency (see Hotta and Cardoso Neto (1993) and Lütkepohl (2010)). Alternatively, the MIxed DAta Sampling approach (MIDAS) introduced by Ghysels and his coauthors has proved to be useful (see Ghysels et al. (2002) and Ghysels et al. (2007)); more specifically, in the forecasting framework, several empirical papers have shown the pertinence of incorporating financial information at the time of predicting macroeconomic fluctuations using a MIDAS-based approach, mainly in the US economy (see for example Clements and Galvão (2008)) but also in the euro area (see Marcellino and Schumacher (2010) for Germany or Ferrara and Marsilli (2013) for other euro area countries). Indeed, in the presence of various sampling frequencies, the MIDAS approach avoids data temporal aggregation and the associated loss of information by using parsimoniously parametrized weight functions that specify the importance of each covariate along their past.

In this paper, we aim at assessing the impact of financial volatility on output growth in three advanced economies (US, UK, and France) via the introduction of an extended MIDAS model capable of putting together daily and monthly sampled explanatory variables in order to predict the quarterly GDP growth rate; this modeling approach is explained in detail in Section 1. In Section 2 we use two well-known daily sampled financial ingredients, namely, commodity and stock prices, combined with a monthly industrial production index to empirically show the gain in prediction performance for various forecasting horizons, when daily financial volatility is included in the mixed-frequency models. Our study provides conclusive empirical proof that this approach increases the predictive accuracy during a period that includes the last Great Recession for the three considered countries.

1 The econometric model

In this paper, we assess the predictive content of the daily volatility of financial variables regarding the gross domestic product (GDP) using the MIDAS approach introduced in Ghysels et al. (2002). This forecasting strategy allows the use of explaining variables sampled at different frequencies avoiding at the same time the loss of information associated to data temporal aggregation; this is achieved by exploiting parsimoniously parametrized weight functions that specify the importance of each covariate along their past in an economically reasonable fashion. A major motivation for exploring this scheme is the well known fact that hard data, generally sampled with monthly frequency, convey additional information to anticipate the GDP that is, in turn, quarterly measured. Using the MIDAS approach we will go a step further and will incorporate in the forecasting setup a combination of monthly and daily sampled covariates. This approach has already been studied by Andreou et al. (2013) who show the pertinence, from the point of view of increase in the forecasting power, of combining monthly macroeconomic indicators with daily financial explaining data. The GDP prediction proposed in their work is constructed via the weighted combination of a number of individual MIDAS based forecasts obtained by using a single financial covariate at a time. The authors have indeed used an important financial dataset in order to construct a rich family of separate MIDAS forecasts; their combination yields satisfactory results and shows the predictive relevance of daily information in the macroeconomic context. Our work can be seen as an extension, focusing on the financial volatility as predictor of the real GDP growth during the Great Recession.

Let Y_t^Q be a quarterly sampled stationary variable that we aim at predicting, X_t^M is a vector of N_M stationary monthly quoted variables, and X_t^D is a vector of N_D stationary daily variables. We propose the following extended MIDAS model enabling the mixing of daily and monthly information:

$$Y_t^{\mathrm{Q}} = \alpha + \sum_{i=1}^{N_D} \beta_i \; m^{K_D}\left(\theta_i\right) \; X_{i,t}^{\mathrm{D}} \; + \sum_{j=1}^{N_M} \gamma_j \; m^{K_M}\left(\omega_j\right) \; X_{j,t}^{\mathrm{M}} \; + \phi \; Y_{t-1}^{\mathrm{Q}} + \varepsilon_t, \tag{1}$$

where ε_t is a white noise process with constant variance and α, β, θ, γ, and ω are the regression parameters to be estimated. We also include a first order autoregressive term in the expression (1) as it has been shown that it generally improves forecasting accuracy based on leading indicators (see for example Stock and Watson (2003)).

The $m^K(\cdot)$ function in equation (1) prescribes the polynomial weights that allow the frequency mixing. The main idea behind the MIDAS specification consists of smoothing the past values of each covariate $X_{i,t}^{\kappa}$ by using polynomials $m^K(b)$ of the form

$$m^K\left(b\right) := \sum_{k=1}^{K} \frac{f(\frac{k}{K}, b)}{\sum_{k=1}^{K} f(\frac{k}{K}, b)} \; L^{(k-1)/\kappa}, \tag{2}$$

where K is the cardinality of the data set window on which the regression is based and κ is the number of realizations of $X_{i,t}^{\kappa}$ during the period $[t-1, t]$; for example, in equation (1), $\kappa = \mathrm{M} = 3$ for $X_{j,t}^{\mathrm{M}}$. It is clear from (2) that the regression model is only influenced by the last K sample values. Note that the window size K is an exogenous parameter chosen by the user, whereas the coefficient b is part of the estimation problem. L is the lag operator such that $L^{s/\kappa} X_t^{\kappa} = X_{t-(s/\kappa)}^{\kappa}$, and $f(\cdot)$ is the weight function that can be chosen out of various parametric families. As in Ghysels et al. (2007), we take as $f(\cdot)$ the following Beta restricted function:

$$f(z, b) = b \; (1-z)^{b-1}. \tag{3}$$

While other weight function specifications often employed in the literature like the exponential

Almon form, relies on the use of at least two parameters, the Beta restricted function involves only one parameter. Additionally it imposes decreasing weight values which is a desirable feature in view of the direct multistep forecasting setup that we adopt later on in the empirical application that we will carry out in Section 2.

As one of the main objectives of our work consists in providing evidence of the macroeconomic predictive content of financial volatilities, a crucial issue is the estimation of volatility. Given that volatility is not directly observable, several methods have been developed in the literature to estimate it. The most straightforward approach to this problem relies in the use of the absolute value of the returns as a proxy for volatility; unfortunately, the results obtained this way are generally very noisy (see Andersen and Bollerslev (1998)). This difficulty can be partially fixed by using an average of this noisy proxy over a given period; this method yields one of the most widely used notion of volatility, namely the *realized* volatility (as used, for example, in Chauvet et al. (2012)). For example, for a given quarter t, the realized volatility RV_t can be estimated as

$$RV_t = \left(\sum_{s=1}^{n_t} {r_s^D}^2 \right)^{1/2}, \tag{4}$$

where (r_s^D) are the daily returns and n_t is the number of days for the quarter t. Since our goal is working with daily financial volatility, the realized approach would require intraday data whose availability may be an issue and that, additionally, requires a delicate handling (overnight effects, price misrecordings, etc); see Barndorff-Nielsen et al. (2009). An alternative convenient approach appears to be the volatility filtered out of a GARCH-type parametric family (Engle (1982), and Bollerslev (1986)). The AR(p)-GARCH(r,s) specification is given by

$$\begin{cases} r_t^D &= \psi_0 + \psi_1 \, r_{t-1}^D + \cdots + \psi_p \, r_{t-p}^D + w_t, \\ w_t &= v_t^D \, \eta_t, \\ (v_t^D)^2 &= c + \sum_{i=1}^{\mathrm{r}} a_i \, w_{t-i}^2 + \sum_{j=1}^{\mathrm{s}} b_j \, (v_{t-j}^D)^2, \end{cases} \tag{5}$$

where ψ_0 is a constant, where $\psi = (\psi_1, \ldots, \psi_p)$ is a p-vector of autoregressive coefficients and where $\{\eta_t\} \sim \mathrm{WN}(0,1)$. In order to ensure the existence of a unique stationary solution and the positivity of the volatility, we assume that $a_i > 0$, $b_j \geq 0$ and $\sum_{i=1}^{\mathrm{r}} a_i + \sum_{j=1}^{\mathrm{s}} b_j < 1$. Estimated daily volatilities $(\hat{v}_t^D)$ stemming from equation (5) will be considered as explanatory variables of the macroeconomic fluctuations using the MIDAS regression equation (1), with $X_{i,t}^D = \hat{v}_{i,t}^D$.

Finally, when using general regression models for forecasting purposes at a given horizon $h > 0$, forecasters can either predict covariates or implement direct multi-step forecasting (see for example Chevillon (2007) for a review on this point). The idea behind direct multi-step forecasting is that the potential impact of specification errors on the one-step-ahead model can be reduced by using the same horizon both for estimation and for forecasting at the expense of estimating a specific model for each forecasting horizon. In our work we adopt the direct multi-step forecasting and assume that the predictor $Y^Q_{t+h|t}$ of the GDP quarterly growth rate, for any forecasting horizon h, is given by

$$Y^Q_{t+h|t} = \hat{\alpha}^{(h)} + \sum_{i=1}^{N_D} \hat{\beta}_i^{(h)}\; m^{K_D}(\hat{\theta}_i^{(h)})\, \hat{v}^D_{i,t} + \sum_{j=1}^{N_M} \hat{\gamma}_j\; m^{K_M}(\hat{\omega}_j^{(h)})\, X^M_{j,t}\; + \hat{\phi}^{(h)}\, Y^{\mathrm{Q}}_t, \tag{6}$$

where $(\hat{\alpha}^{(h)}, \hat{\beta}_1^{(h)}, \ldots, \hat{\beta}_{N_D}^{(h)}, \hat{\theta}_1^{(h)}, \ldots, \hat{\theta}_{N_D}^{(h)}, \hat{\gamma}_1^{(h)}, \ldots, \hat{\gamma}_{N_M}^{(h)}, \hat{\omega}_1^{(h)}, \ldots, \hat{\omega}_{N_M}^{(h)}, \phi^{(h)})$ are the non-linear least squares estimators (this yields $2N_D + 2N_M + 2$ parameters that need to be estimated).

2 Empirical results

In this section we focus on the GDP growth prediction. We implement the model previously introduced in equation (6) in order to assess the forecasting ability of the volatility of two financial variables, namely commodity and stock prices (i.e. $N_D = 2$) in comparison with the monthly industrial production (i.e. $N_M = 1$).

The variable that we want to predict is the quarterly growth rate of the real GDP (expressed in percentage and denoted GDP_t) of three countries: US, France, and the UK, as released by the corresponding national offices of statistics in July 2013. We consider as explanatory daily variables the CRB index of commodity prices and the main national stock price indices of those three countries, namely the S&P500, the CAC40, and the FTSE100, that we denote generically as CRB_t and SP_t. Details concerning sources and the datasets are given in Appendix A in Table 2; all the data have been downloaded from Datastream. Note that stock prices for France and the UK begin later than for the US (1987 instead of 1975). For all daily returns of financial variables, we estimate their volatility on the available sample by using a AR(1)-GARCH(1,1) specification as in the equation (5). The model orders have been selected using the Bayes Information Criterion (BIC). Since we are using a standard maximum likelihood estimator for the GARCH process and not a robust one (see for example, Charles and Darné (2005), or Carnero et al. (2012)) we have smoothed out outliers from all returns via a 99.5% Winsorization (for instance the *Black Monday* outlier in the S&P500 series occurring October 19$^{\text{th}}$, 1987). Estimates of daily volatility for both variables, denoted as ($\hat{v}^{D}_{t,CRB}$) and ($\hat{v}^{D}_{t,SP}$), are presented in Appendix B in Figure 4. It is worth noting that, as it usually happens with financial time series, periods of high volatility are clustered in time; nevertheless, the high volatility clusters do not occur at the same time for both time series. The volatility of stock prices presents a huge peak during the recent financial crisis, as well as several smaller peaks related to specific events (Asian crisis, burst of the internet bubble, *etc.*). Since we focus on the post 1973 oil crisis period (from 1975 to 2010), the commodity volatility exhibits only one main peak related to the recent financial crisis. Some specific events also drive commodity volatility dynamics such as the second oil shock in the early 1980s or the Asian crisis in the late 1990s. The information conveyed by both volatilities does not seem redundant in spite of a recent increase in their correlation (see *e.g.* Creti et al. (2013)) and both variables are potentially useful in explaining GDP growth.

As monthly explanatory variable in the MIDAS regression (6) we use the Industrial Production manufacturing Index (IPI) that is well known by practitioners to be informative about the evolution of macroeconomic variables in general and as to the dynamics of the GDP growth in particular. We consider the monthly IPI growth rate, denoted IPI_t. The time series dataset used in this empirical study is described in Table 2. Both GDP and IPI for the three countries are represented in Appendix C in Figure 5.

In our study we carry out parameter estimation using the periods 1976q1-2006q4 for the US and 1988q1-2006q4 for France and the UK, then we implement an out-of-sample experience over the period 2007q1 - 2010q4 that includes the Great Recession. Concerning the forecasting experiment, given that financial data are always available the last working day of any given month, we suppose that forecasts for a specific quarter are computed at the end of each month, for 12 horizons that range 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 any time t the MIDAS regression optimally takes advantage of the fluctuations of the last $K_M = 6$ for the monthly series IPI_t and $K_D = 90$ for financial covariates $\hat{v}^{D}_{t,CRB}$ and $\hat{v}^{D}_{t,SP}$. As we have chosen a direct multi-step forecasting approach, model parameters are estimated separately for each prediction horizon h, as in equation (6).

In a first step, we assess the specific impact of both financial volatilities on the GDP growth process through a standard MIDAS model that relates daily variables with a quarterly variable. Thus, the first model that we estimate, denoted **Model $\mathbf{M_d}$**, contains as regressors the daily volatilities of both financial series, namely $\hat{v}^D_{t,CRB}$ and $\hat{v}^D_{t,SP}$:

$$\mathrm{GDP}_{t+h|t} = \hat{\alpha}^{(h)} + \hat{\beta}_1^{(h)}\ m^{K_D}(\hat{\theta}_1^{(h)})\,\hat{v}^D_{t,CRB} + \hat{\beta}_2^{(h)}\ m^{K_d}(\hat{\theta}_2^{(h)})\,\hat{v}^D_{t,SP} + \hat{\phi}^{(h)}\,\mathrm{GDP}_t. \tag{M$_\mathrm{d}$}$$

The second model, denoted **Model $\mathbf{M_m}$**, contains only as regressors the monthly growth rate of the IPI:

$$\mathrm{GDP}_{t+h|t} = \hat{\alpha}^{(h)} + \hat{\gamma}^{(h)}\ m^{K_M}(\hat{\omega}^{(h)})\,\mathrm{IPI}_t + \hat{\phi}^{(h)}\,\mathrm{GDP}_t. \tag{M$_\mathrm{m}$}$$

Explaining GDP growth using industrial production is standard in the empirical literature on short-term macroeconomic forecasting, especially when using bridge equations (see for example Diron (2008), or Barhoumi et al. (2012)). However, the monthly IPI series is generally aggregated before using it in quarterly equations. Here, by using a standard MIDAS equation, we allow for different weights concerning the contribution of monthly IPI to GDP growth, adding thus more flexibility to the model.

The third model, denoted **Model $\mathbf{M_{dm}}$**, contains as regressors both daily volatilities and the monthly IPI:

$$\begin{aligned}\mathrm{GDP}_{t+h|t} = \hat{\alpha}^{(h)} + \hat{\beta}_1^{(h)}\ m^{K_D}(\hat{\theta}_1^{(h)})\,\hat{v}^D_{t,CRB} + \hat{\beta}_2^{(h)}\ m^{K_D}(\hat{\theta}_2^{(h)})\,\hat{v}^D_{t,SP} \\ + \hat{\gamma}^{(h)}\ m^{K_M}(\hat{\omega}^{(h)})\,\mathrm{IPI}_t + \hat{\phi}^{(h)}\,\mathrm{GDP}_t.\end{aligned} \tag{M$_\mathrm{dm}$}$$

To assess the forecasting accuracy of each model, we compute the root mean square forecasting errors (RMSFE), for all forecasting horizons h, based on differences between realized values $\mathrm{GDP_{t+h}}$ and forecasted values $\mathrm{GDP}_{t+h|t}$ on the 16 point forecasts over the 4 years out of sample from 2007q1 to 2010q4. In order to have a measure of the real predictive ability of financial market volatility, we also provide forecasting results using a simple autoregressive model AR(1) as a benchmark:

$$\mathrm{GDP}_{t+h|t} = \hat{\alpha}^{(h)} + \hat{\phi}^{(h)}\,\mathrm{GDP}_t. \tag{AR}$$

We note that an autoregressive element has always been added in the three models to play the role of control variable and to potentially improve the prediction. Comparing the obtained results with those using Model (AR) helps us in measuring the real contribution of the explanatory variables and financial data in particular.

For each model (**Model $\mathbf{M_d}$**, **Model $\mathbf{M_m}$**, **Model $\mathbf{M_{dm}}$**) and each forecast horizon h, RMSFE(h) values are presented in Table 1. In addition, RMSFE(h) values, for h ranging from zero to 11/3, are also plotted in Figure 1 for US, in Figure 2 for France and in Figure 3 for the UK.

	Forecasting horizons h											
	0	1/3	2/3	1	4/3	5/3	2	7/3	8/3	3	10/3	11/3
RMSFE(h) for the US												
Model M_d	0.63	0.73	0.77	0.90	0.93	0.97	1.03	1.05	1.08	1.12	1.13	1.12
Model M_m	0.67	0.68	0.76	0.93	1.00	0.99	1.05	1.05	1.05	1.07	1.07	1.07
Model M_{dm}	0.57	0.66	0.71	0.84	0.92	0.93	1.02	1.05	1.04	1.12	1.13	1.14
Model AR	0.86	0.86	0.86	0.99	0.99	0.99	1.07	1.07	1.07	1.09	1.09	1.09
RMSFE(h) for France												
Model M_d	0.61	0.62	0.62	0.69	0.69	0.70	0.82	0.82	0.80	0.98	1.02	0.99
Model M_m	0.51	0.53	0.53	0.70	0.73	0.72	0.78	0.77	0.79	0.88	0.83	0.84
Model M_{dm}	0.48	0.51	0.50	0.61	0.65	0.68	0.80	0.81	0.80	0.89	0.81	0.87
Model AR	0.62	0.62	0.62	0.73	0.73	0.73	0.82	0.82	0.82	0.86	0.86	0.86
RMSFE(h) for the UK												
Model M_d	0.74	0.76	0.78	0.99	1.01	1.04	1.19	1.20	1.22	1.34	1.35	1.37
Model M_m	0.84	0.85	0.91	1.04	1.10	1.23	1.30	1.30	1.27	1.29	1.32	1.31
Model M_{dm}	0.71	0.72	0.80	0.97	1.02	1.04	1.14	1.17	1.16	1.34	1.32	1.32
Model AR	1.10	1.10	1.10	1.29	1.29	1.29	1.36	1.36	1.36	1.37	1.37	1.37

TABLE 1: RMSFE(h) for quarterly GDP growth. The forecasting horizon h is measured in quarters.

As expected, RMSFE(h) for all models and all countries decrease when h tends to zero, reflecting the use of an information set of increasing size. Indeed, RMSFE(h) are more than halved when h goes from 8/3 to zero. Especially, when $2/3 \leq h \leq 4/3$, we observe a strong negative slope, visible for all models. This is due to the integration of the newly available GDP growth figure of the previous quarter.

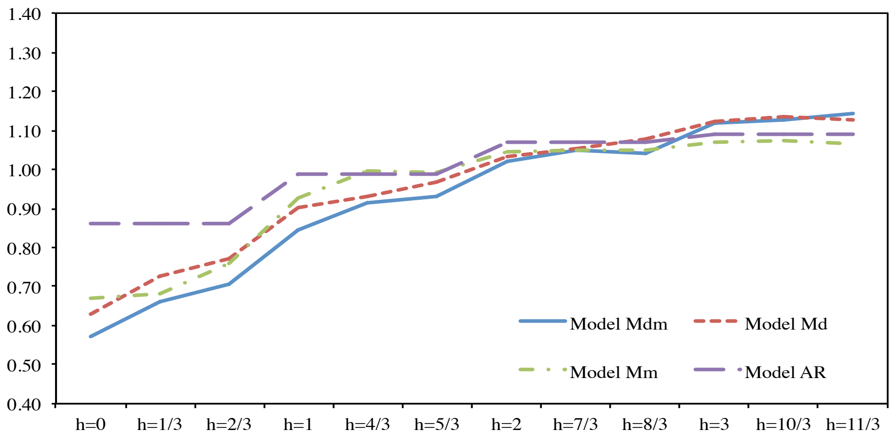

FIGURE 1: RMSFE(h) for US

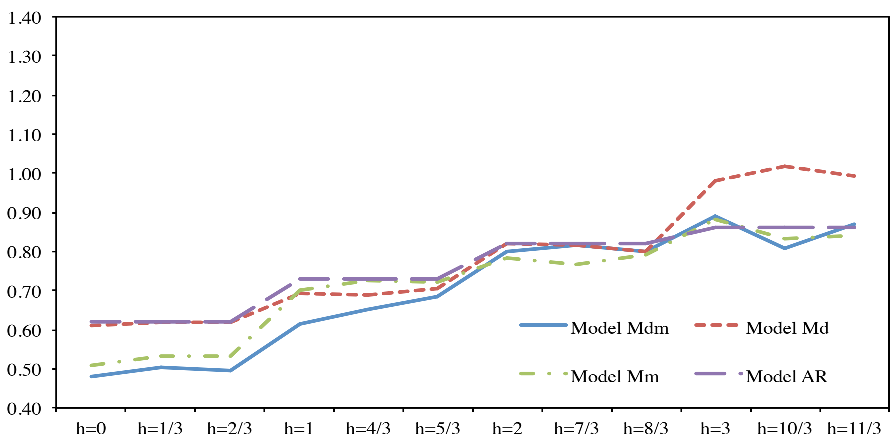

FIGURE 2: RMSFE(h) for France

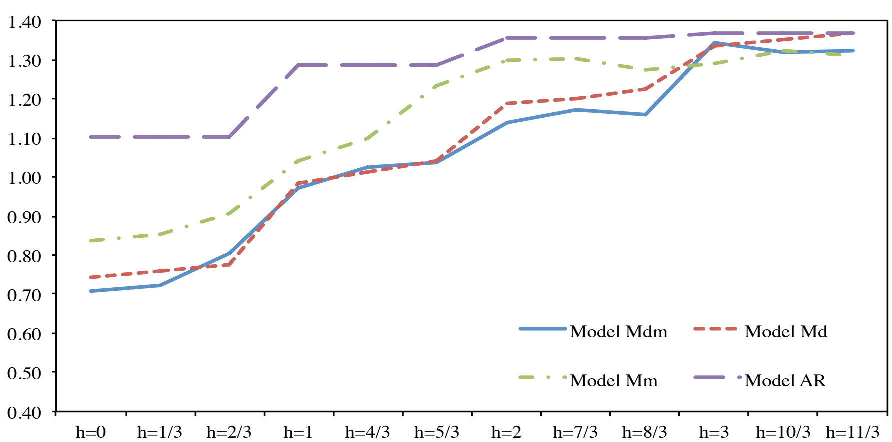

FIGURE 3: RMSFE(h) for UK

An analysis of Figure 1, Figure 2, and Figure 3 shows that the **Model** $\mathbf{M_{dm}}$ based on daily financial volatilities and monthly IPI unanimously provides the best results for all horizons h for the three economies analyzed. This result proves in a robust fashion that combining information coming from both macroeconomic and financial sources appears to be a good strategy when forecasting GDP. We are in agreement in this point with much of the literature on macroeconomic forecasting and nowcasting that underlines the usefulness of either combining information (for example through dynamic factor models, see e.g. Giannone et al. (2008)) or combining forecasts (see *e.g.* Timmermann (2006)). In fact, the forecasting gain obtained by using the **Model** $\mathbf{M_{dm}}$ becomes important already for $h \leq 1$. We also note that between $h = 4/3$ and $h = 7/3$, the contribution of financial volatilities to the forecasting accuracy is remarkable, specially for the US and the UK economies, as RMSFE(h) stemming from **Model** $\mathbf{M_{dm}}$ and **Model** $\mathbf{M_d}$ are almost similar. This result is interesting for practitioners in the sense that using industrial production to predict GDP with a lead of four to seven months does not appear useful; only financial volatilities help in this range of horizons. Nevertheless, we note that the forecasting results for the UK are leaded by the financial **Model** $\mathbf{M_d}$ while it appears that the **Model** $\mathbf{M_m}$ does not really contribute, not even for short term horizons, to the predictive accuracy of the combined **Model** $\mathbf{M_{dm}}$. These results suggest that financial variables play an important role in forecasting the real UK economy. This has often been underlined in the literature; we refer, among others, to Simpson et al. (2001).

When we are close to the target date, that is during the quarter before the release (i.e. $h \leq 1$), the IPI tends to increase its impact on the forecast in particular in the case of the US and France. This stylized fact has been also observed in empirical papers pointing out the increasing role of hard variables on macroeconomic forecasts when we are close to the release date, while financial variables have a stronger impact for longer horizons (we refer for example to Angelini et al. (2011)). Our study shows that the information contained on the industrial output series cannot replace the one associated to financial volatility; both sources of information are playing an important role, but at various horizons.

Conclusion

In this paper, we assess the predictive content of financial volatility on the economic growth during the 2007-2010 period, that includes the Great Recession. In this respect, we put forward an extended MIDAS model that integrates explanatory variables at both daily and monthly frequencies to predict the quarterly GDP growth. We show that adding daily financial volatility of stock and commodity prices increases the forecasting accuracy in comparison with a benchmark model that includes only industrial production as an explanatory variable. Moreover, our results indicate that an extended MIDAS model that includes both financial volatilities and industrial production is the most adequate approach for all forecasting horizons. Additionally, we note that between 4 and 7 months before the target date, there is no predictive gain in including industrial production and purely financial information is sufficient.

References

Ahn, E. S. and Lee, J. M. (2006). Volatility relationship between stock performance and real output. *Applied Financial Economics*, 16(11):777–784.

Andersen, T. G. and Bollerslev, T. (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International Economic Review*, 39(4):885–905.

Andreou, E., Ghysels, E., and Kourtellos, A. (2013). Should macroeconomic forecasters use daily financial data and how? *Journal of Business and Economic Statistics*, 31(2):240–251.

Angelini, E., Camba-Mendez, G., Giannone, D., Reichlin, L., and Rünstler, G. (2011). Short-term forecasts of euro area GDP growth. *The Econometrics Journal*, 14(1):C25–C44.

Barhoumi, K., Darné, O., Ferrara, L., and Pluyaud, B. (2012). Monthly gdp forecasting using bridge models: Application for the french economy. *Bulletin of Economic Research*, 64:s53–s70.

Barndorff-Nielsen, O. E., Hansen, P. R., Lunde, A., and Shephard, N. (2009). Realized kernels in practice: trades and quotes. *Econometrics Journal*, 12(3):C1–C32.

Bellégo, C. and Ferrara, L. (2012). Macro-financial linkages and business cycles: A factor-augmented probit approach. *Economic Modelling*, 29(5):1793–1797.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3):307–327.

Carnero, M. A., Peña, D., and Ruiz, E. (2012). Estimating GARCH volatility in the presence of outliers. *Economics Letters*, 114(1):86–90.

Charles, A. and Darné, O. (2005). Outliers and GARCH models in financial data. *Economics Letters*, 86(3):347–352.

Chauvet, M., Senyuz, Z., and Yoldas, E. (2012). What does financial volatility tell us about macroeconomic fluctuations? Working Paper 9, Federal Reserve Board.

Chevillon, G. (2007). Direct multi-step estimation and forecasting. *Journal of Economic Surveys*, 21(4):746–785.

Claessens, S., Kose, M. A., and Terrones, M. E. (2012). How do business and financial cycles interact? *Journal of International Economics*, 87(1):178–190.

Clements, M. P. and Galvão, A. B. (2008). Macroeconomic forecasting with mixed-frequency data. *Journal of Business and Economic Statistics*, 26(4):546–554.

Creti, A., Joëts, M., and Mignon, V. (2013). On the links between stock and commodity markets' volatility. *Energy Economics*, (37):16–38.

Diron, M. (2008). Short-term forecasts of euro area real GDP growth: an assessment of real-time performance based on vintage data. *Journal of Forecasting*, 27(5):371–390.

Engle, R. F. (1982). Autoregressive Conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 50(4):pp. 987–1007.

Ferrara, L. and Marsilli, C. (2013). Financial variables as leading indicators of GDP growth: Evidence from a MIDAS approach during the Great Recession. *Applied Economics Letters*, 20(3):233–237.

Ghysels, E., Santa-clara, P., and Valkanov, R. (2002). The MIDAS touch : Mixed data sampling regression models. mimeo, Chapel Hill, N.C.

Ghysels, E., Sinko, A., and Valkanov, R. (2007). MIDAS regressions: Further results and new directions. *Econometric Reviews*, 26(1):53–90.

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

Hamilton, J. D. (2003). What is an oil shock? *Journal of Econometrics*, 113(2):363–398.

Hamilton, J. D. and Lin, G. (1996). Stock market volatility and the business cycle. *Journal of Applied Econometrics*, 11(5):573–593.

Hotta, L. K. and Cardoso Neto, J. (1993). The effect of aggregation on prediction in autoregressive integrated moving-average models. *Journal of Time Series Analysis*, 14(3):261–269.

Kilian, L. (2008). The economic effects of energy price shocks. *Journal of Economic Literature*, 46(4):871–909.

Lütkepohl, H. (2010). Forecasting Aggregated Time Series Variables. *OECD Journal: Journal of Business Cycle Measurement and Analysis*, 2:1–26.

Marcellino, M. and Schumacher, C. (2010). Factor MIDAS for nowcasting and forecasting with ragged-edge data: A model comparison for German GDP. *Oxford Bulletin of Economics and Statistics*, 72(4):518–550.

Simpson, P. W., Osborn, D. R., and Sensier, M. (2001). Forecasting UK industrial production over the business cycle. *Journal of Forecasting*, 20(6):405–424.

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

Timmermann, A. (2006). Forecast combinations. In *Handbook of Economic Forecasting*, chapter 4. Elsevier edition.

A Description of variables involved in the MIDAS regressions

Quarterly output		
GDP	Real US GDP growth (*Bureau of Economic Analysis*)	1976q1:2010q4
	French GDP growth (*INSEE*)	1988q1:2010q4
	UK GDP growth (*Office for National Statistics*)	1988q1:2010q4
Daily volatilities		
CRB	CRB spot price index (*Commodity Research Bureau*)	01jan1964:31dec2010
SP	S&P500 index (*Standard & Poors*)	01jan1964:31dec2010
	CAC40 index (*Euronext Paris*)	03aug1987:31dec2010
	FTSE100 index (*FTSE*)	01jan1987:31dec2010
Monthly series		
IPI	US industrial production index manufacturing (*Fed. Reserve*)	jan1976:dec2010
	French industrial production index manufacturing (*INSEE*)	jan1988:dec2010
	UK industrial production index manufacturing (*ONS*)	jan1988:dec2010

Table 2: Description of indicators and covariates

B Daily volatilities of the four financial explanatory variables

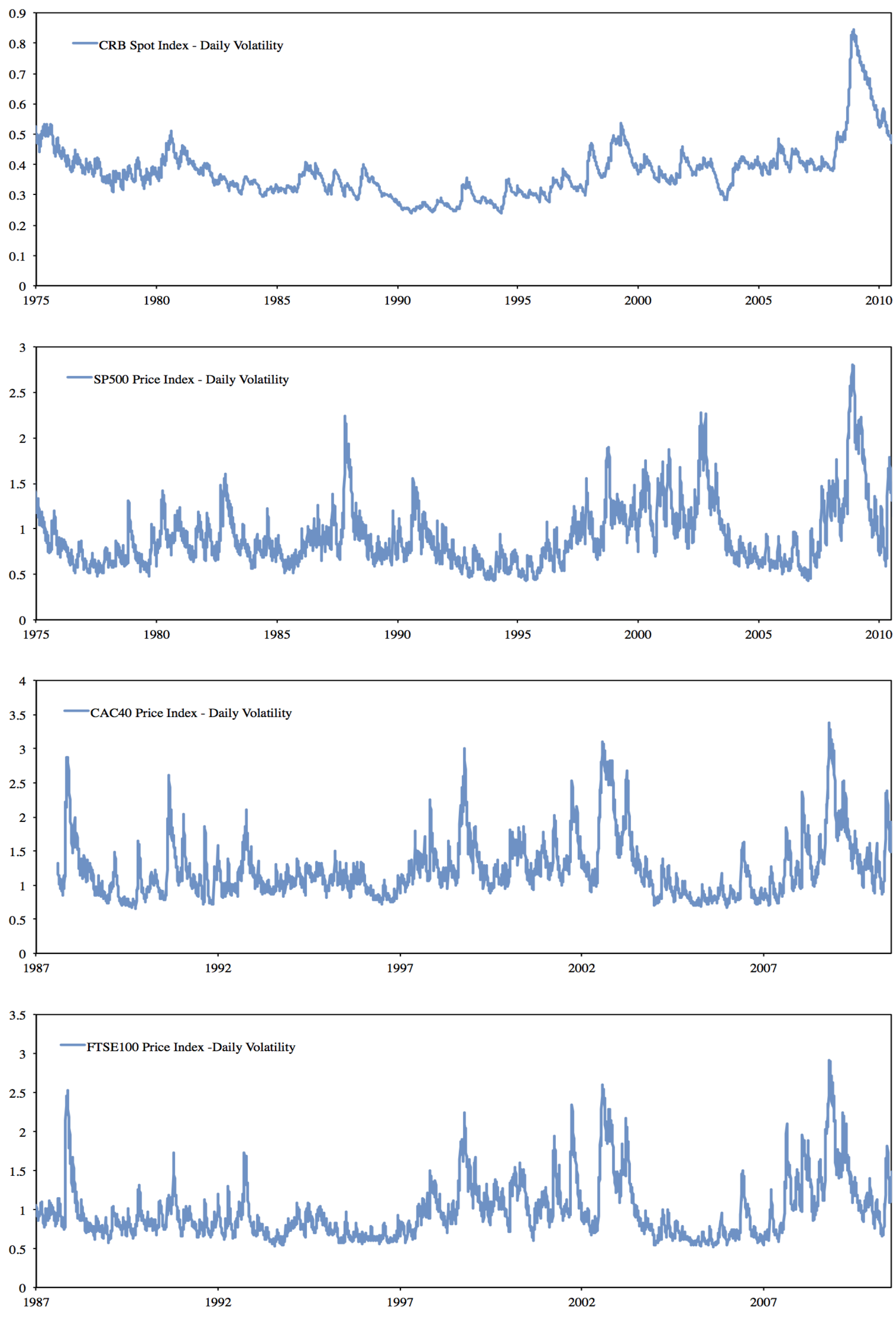

Figure 4: Volatilities estimated using GARCH models, CRB on the top then then main national stocks index, namely S&P500, CAC40 and FTSE100 on the bottom

C Growth rates of GDP and IPI

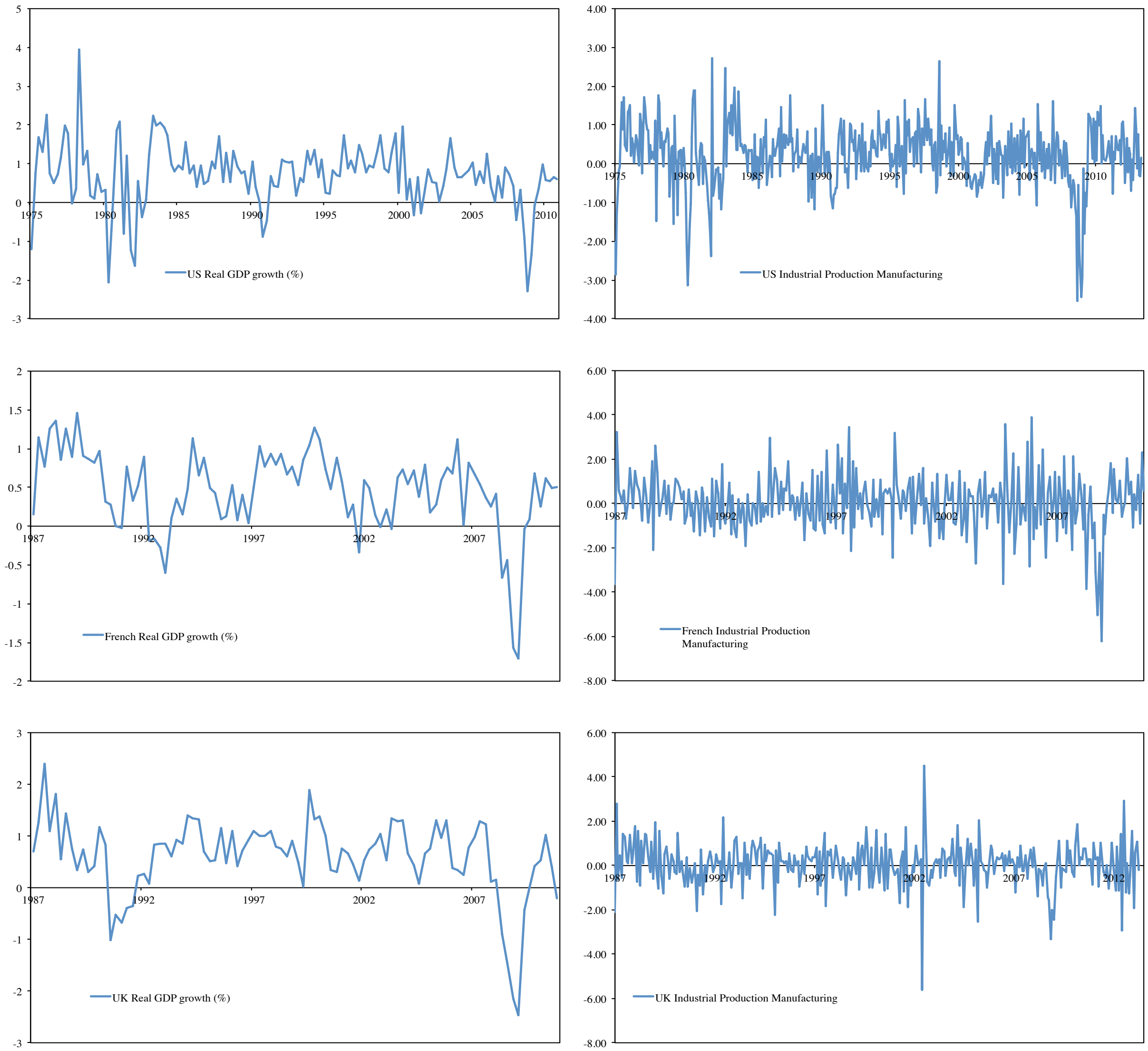

Figure 5: Growth rates of the GDP and the IP manufacturing index for the US (top), France, and the UK.

Documents de Travail

440. P. A. Pintus and J. Suda, “Learning Leverage Shocks and the Great Recession,” August 2013

441. G. Cette, J. Lopez et J. Mairesse, “ Upstream product market regulations, ICT, R&D and productivity,” August 2013

442. M. Juillard, H. Le Bihan and S. Millard, “Non-uniform wage-staggering: European evidence and monetary policy implications,” August 2013

443. G. Cheng, “A Growth Perspective on Foreign Reserve Accumulation,” August 2013

444. D. Wesselbaum, “Procyclical Debt as Automatic Stabilizer,” September 2013

445. A. Berthou and V. Vicard, “Firms' Export Dynamics: Experience vs. Size,” September 2013

446. S. Dubecq, A. Monfort, J-P. Renne and G. Roussellet, “Credit and Liquidity in Interbank Rates: a Quadratic Approach,” September 2013

447. V. Bignon, R. Esteves and A. Herranz-Loncán, “Big Push or Big Grab? Railways, Government Activism and Export Growth in Latin America, 1865-1913,” September 2013

448. C. D’Avino, “Net interoffice accounts of global banks: the role of domestic funding,” September 2013

449. J. Dugast, “Limited Attention and News Arrival in Limit Order Markets,” October 2013

450. V. Bignon, R. Breton and M. Rojas Breu, “Currency Union with or without Banking Union,” October 2013

451. M. Crozet, E. Milet and D. Mirza, “The Discriminatory Effect of Domestic Regulations on International Trade in Services: Evidence from Firm-Level Data,” October 2013

452. P. Bacchetta, K. Benhima, and Y. Kalantzis, “Optimal Exchange Rate Policy in a Growing Semi-Open Economy,” October 2013

453. M. Beine, J-C. Bricongne and P. Bourgeon, “Aggregate Fluctuations and International Migration,” October 2013

454. L. Ferrara, C. Marsilli and J.-P. Ortega, “Forecasting growth during the Great Recession: is financial volatility the missing ingredient?,” October 2013

Pour accéder à la liste complète des Documents de Travail publiés par la Banque de France veuillez consulter le site : www.banque-france.fr

For a complete list of Working Papers published by the Banque de France, please visit the website: www.banque-france.fr

Pour tous commentaires ou demandes sur les Documents de Travail, contacter la bibliothèque de la Direction Générale des Études et des Relations Internationales à l'adresse suivante :

For any comment or enquiries on the Working Papers, contact the library of the Directorate General Economics and International Relations at the following address :

BANQUE DE FRANCE
49- 1404 Labolog
75049 Paris Cedex 01
tél : 0033 (0)1 42 97 77 24 ou 01 42 92 63 40 ou 48 90 ou 69 81
email : 1404-ut@banque-france.fr