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

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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 model that allows the forecasting of the quarterly output growth rate 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.

1. 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 while 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-swtiching modeling while 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 (MIDAS) approach introduced by Ghysels and his coauthors has proved to be useful (see Ghysels et al. (2004) 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.

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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.

2. 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. (2004). 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:

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

where ε_t is a white noise process with constant variance and $\alpha, \beta, \theta, \gamma$, and ω are the regression parameters to be estimated. We also include a first order autoregressive term in 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 $\mathrm{m}^K(\cdot)$ function in Eq. (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 $\mathrm{m}^K(b)$ of the form

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

where K is the cardinality of the dataset 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 Eq. (1), $\kappa = \mathrm{M} = 3$ for $X_{j,t}^{\mathrm{M}}$. It is clear from Eq. (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 $f(\cdot)$ as 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 notions 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 as

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

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 $\left(\hat{v}_t^D\right)$ stemming from Eq. (5) will be considered as explanatory variables of the macroeconomic fluctuations using the MIDAS regression Eq. (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