Forecasting GDP Growth using Financial Information

Mamadou Ndiaye SENE (✉ mamadounsene@gmail.com)

University of Tunis El Manar: Universite de Tunis El Manar

Research Article

Keywords: Econometrics, Forecasting, Fluctuations, Daily Volatility, Mixed Frequency Models, Markets

Posted Date: February 21st, 2022

DOI: <https://doi.org/10.21203/rs.3.rs-1158364/v1>

License: This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Forecasting GDP Growth using Financial Information

Mamadou Ndiaye SENE¹

ABSTRACT

The shocks that occur in periods of instability in financial markets affect the effective implementation that would be subject to appropriate macroeconomic policies. Researchers have developed several approaches to monitor macroeconomic policies concerned with the goal of stabilizing and strengthening the global financial system. The 2007 financial crisis revealed the limits of the proposed approaches, which designed to analyse and forecast the economic fluctuations. Other approaches, including the mixed frequency data models, have been put forward to address the limitations the existing forecasting models by taking into account the interactions between the real and financial sectors. The information on the equity and commodity markets increase the predictive capacities of models and thereby can be used to forecast the fluctuations of GDP growth. The present paper applies a model-independent data assimilation (MIDAS), which is embedded in the mixed frequency data models, to forecast the fluctuations in the economic growth of five developed countries, namely the United States, France, Germany, United Kingdom and Japan. The results show that, taking into account the volatility of financial market indicators enable to provide accurate projections of the economic growth. Furthermore, the integration of the autoregressive component in the MIDAS model strengthens its predictive capacity over the forecast period.

Keywords: Econometrics, Forecasting, Fluctuations, Daily Volatility, Mixed Frequency Models, Markets.

¹ University of Tunis El Manar (UTM), Tunisia; Faculty of Economics and Management (FSEGT); Laboratory for Research on Quantitative and Development Economics (LAREQUAD). mamadounsene@gmail.com

1. INTRODUCTION

The relationship between the real economy and financial markets has been and continues to be an issue of considerable interest and concern to all countries, drawing attention of the economic researchers, policymakers, and international institutions, including the International Monetary Fund (IMF) and World Bank. The analysis of the role of financial markets in explaining the real economy took off in the early 1980s, notably with the work of Bernanke ([1983](#)). The financial crises² that have occurred have reinforced this renewed interest and raised questions about taking into account the role of financial markets in forecasts production growth, fostering a better control of systemic risk.

Drawing on the work of Friedman & Schwartz ([1963](#)) on explaining the Great Depression of the 1930s, Bernanke ([1983](#)) has concluded that shocks in the financial markets are responsible for macroeconomic fluctuations. Other researchers, including Fama ([1985](#)), Hamilton ([1987](#)), Haubrich ([1987](#)), Gertler ([1988](#)), Bernanke, Gertler & Gilchrist (BGG, [1996](#), [1999](#)), have highlighted that financial information is an important component that explains economic fluctuations and macroeconomic balance. In his seminal work, Stock & Watson ([2003](#)) has shown that financial aggregates (share and commodity prices, money supply) improve the performance of models forecasting GDP growth and inflation. Hamilton ([2003](#)) has analyzed the non-linear relationship between commodity prices and GDP growth using an autoregressive Markov-Switching model and found that oil shocks affect economic activity, through the consumer spending of households and businesses. Moreover, Kilian ([2008](#)) has found that notes more generally that shocks from the energy sector generally help reduce economic fluctuations. The issue relating to the financial accelerator has also been raised several researchers (Jerman & Quadrini, [2012](#) ; Costas, [2018](#)). Foroni and Massimiliano ([2012](#)) have considered weekly financial variables in the banking market to illustrate the relationship between the interest rate market and economic activity in the euro area. Others (Ferrara & Marsilli, [2013](#) and Ferrara, Marsilli & Ortega, [2014](#)) have inspired from the studies on forecasting GDP growth during the Great Recession to show the performance of forecasting models in industrialized countries. Their findings reveal that the GDP growth forecasting steadily improve when the volatility of financial

² The Debt Crisis in Mexico (1982), the stock market crash (1987) and the financial crisis of 2007.

variables is taken into account, using mixed frequency data models. Recently, Yan-ran & Qiang Ji (2019) have found, through a multidimensional analysis, that forecasting the volatility of oil prices allows better anticipation of macroeconomic fluctuations.

Two mechanisms of transmitting financial market fluctuations on economic activity flowing from the above-mentioned studies are worthy of consideration. The first is based on the intrinsic relationship between financial and economic activity indicators, by the linear and/or non-linear modelling (Stock & Watson, 2003; Ahn & Lee, 2006; Hamilton & Lin, 1996). The second mechanism refers to the incorporation of volatility into models for forecasting macroeconomic fluctuations (Ferrara, Marsilli & Ortega, 2014). The present paper relates to this second approach, which considers the financial volatility of equity and commodity prices to anticipate quarterly GDP growth.

In empirical work, two types of approaches could be distinguished: i) the technique of aggregating high-frequency financial variables (daily or weekly) explaining the evolution of low-frequency variables (monthly or quarterly); ii) the mixed frequency data models (MIDAS) proposed by Ghysels & al (2004, 2007). The MIDAS models are based on the combination of simultaneous economic and/or financial indicators at different frequencies. More specifically, the present study is inspired from the work of Clements and Galvão (2008), Senyuz & al. (2012) and Ferrara, Marsilli & Ortega (2014), which constitute useful references for the enrichment of this work.

Thus, the methodology consists to use the mixed frequency data models for assessing the impact of (daily) financial volatility on economic activity while taking into account its interactions with other (monthly) economic indicators. The analysis is carried out using data from the financial markets of the United States, France, Great Britain (UK), Germany and Japan. This paper is structured as follow: the first step is to justify the relevance of adopting MIDAS models to perform forecasts of GDP growth, using only economic variables (monthly). The second step consists to show that the performance of MIDAS models when the volatility of financial indicators is also taken into account, in addition.

2. METHODOLOGY

The methodology outlined below is inspired from the work of Ferrara, Marsilli & Ortega (2014), which considers the volatility of financial variables for the prediction of GDP

growth. The MIDAS regression is used for forecasting GDP growth by incorporating the economic and financial variables to measure the performance of each forecasting model across distinct horizons. To this end, the MIDAS and MIDAS-AR models are used, within the framework of forecasts. This enables to show the usefulness of mixed frequency models compared to AR models, but also the importance of taking into account the dynamics of GDP growth in this type of modelling. Furthermore, it will be a question of comparing the forecasts of each model with or without the financial volatilities to assess the relevance of our approach. The style used in this work is in line with that of studies of Kuzin, Marcellino & Schumacher (2009), Foroni & Marcellino (2012), applied to the euro area.

Considering the quarterly GDP growth rate by y_{t_q} , with $t_q = 1, 2, 3, \dots, T_q^y$, a quarterly time index, such as T_q^y is the last quarterly observation of GDP, it consists of forecasting quarterly GDP growth, using a vector of n_M monthly variables, and a vector of n_D daily variables. Daily and monthly variables are stationary, as is quarterly GDP growth.

The MIDAS model can be written follow:

$$y_{t_q} = \alpha_0 + \sum_{i=1}^{n_D} \alpha_i B(L_D; \theta_i) x_{i,t_d+\tau_1}^{(D)} + \sum_{j=1}^{n_M} \beta_j B(L_M; \theta_j) x_{j,t_m+\tau_2}^{(M)} + \varepsilon_{t_q} \quad (1)$$

Where ε_{t_q} is the error term of the model such that $E(\varepsilon_{t_q}) = 0$ et $E(\varepsilon_{t_q}, \varepsilon'_{t_q}) = \sigma_\varepsilon^2$.

$\alpha_0, \alpha_i, \theta_i, \theta_j$ are the parameters of the model to be estimated. $\tau_1 = T_d^{x_i^{(D)}} - T_d^y$; $\tau_2 = T_m^{x_j^{(M)}} - T_d^y$.

Adding an autoregressive process to equation (1) gives the MIDAS-AR model in the following form:

$$y_{t_q} = \alpha_0 + \mu y_{t_q - hz_q} + \sum_{i=1}^{n_D} \alpha_i B(L_D; \theta_i) x_{i,t_d+\tau_1}^{(D)} + \sum_{j=1}^{n_M} \beta_j B(L_M; \theta_j) x_{j,t_m+\tau_2}^{(M)} + \varepsilon_{t_q} \quad (2)$$

With hz_q , the lag in the quarterly GDP growth rate. In this work $hz_q = 1$, due to the nature of the series, and also in conformities with the works of Ferrara & al. (2014) and Stock & Watson (2003). Regarding the beta function $B(L_D; \theta_i)$, we take inspiration from the work of Ferrara, Marsilli & Ortega (2014), who have considered only one parameter

θ in the specification of such function. This approach makes it possible to limit the parameters to be estimated, given a large number of monthly and daily data to be used ($2n_D + 2n_M + 1 + 1$). The beta function is defined as:

$$B(L_h; \theta) = \sum_{k=0}^K c(k, \theta) L_h^k, \quad (3)$$

$$\text{Where : } c(k; \theta) = \frac{f\left(\frac{k}{K}, \theta\right)}{\sum_{k=1}^K f\left(\frac{k}{K}, \theta\right)} \quad (4)$$

With: L , the lag operator such as: $L_h^x x_{t_h}^{(h)} = x_{t_h-x}^{(h)}$; $L_h x_{t_h} = x_{t_h-1}$. K is the number of variables used in the model and h is the number of times $x_{t_h}^{(h)}$ is observed. The function $f(\cdot)$ allows to weigh the variables according to the number of lags (see Ghysels, 2004, Ghysels; Santa-Clara and Valkanov, 2004 and 2007). A simplified form of $f(\cdot)$ was proposed by Ghysels (2004) and gives positive weights that decrease as a function of the number of delays (see Ferrara, Marsilli & Ortega, 2014):

$$f\left(x = \frac{k}{K}, \theta\right) = \theta(1 - x)^{\theta-1} \quad (5)$$

As highlighted, the objective of this work is to show the importance of taking into account information from the financial markets to increase our explanation of macroeconomic fluctuations. It consists concretely in measuring volatility from the series relating to the price indices of equities and commodities, which will be used to refine the forecasts. Volatilities are measured using a GARCH (r, s) model³.

Thus, the stationary return specific to each financial asset r_t follows an ARMA process (p, q) and its volatility v_t is expressed through an ARMA model (p, q) -GARCH (1,1) such as:

$$\begin{cases} r_t = a_0 + \sum_{j=1}^p a_j r_{t-j} + \sum_{k=1}^q \alpha_k \mu_{t-k} + \mu_t, \\ \mu_t = \sqrt{v_t} \eta_t, \\ v_t = b_0 + b_k \mu_{t-1}^2 + \gamma_j v_{t-1}, \end{cases} \quad (5)$$

³ See Engle (1982), Bollerslev (1986), Shimizu (2009), Ling and Li (1997), Francq & Zakoïan (2004), for more details on GARCH modelling.

Where a_0 is a constant; $a = (a_1, \dots, a_p)$ is the p-vector of the autoregressive parameters, and $\alpha = (\alpha_1, \dots, \alpha_q)$ the q-vector of the Moving Average (MA) parameters. $b_0 > 0, b_k \geq 0, k = 1, \dots, s; \gamma_j \geq 0, j = 1, \dots, r$. η_t is white noise.

On the basis of these conditions, it is assumed that the marginal variance $\mathbb{E}(v_t) = v = \sigma^2$ si $(\sum_{k=1}^s b_k + \sum_{j=1}^r \gamma_j) < 1$, to ensure the stationarity and the positivity of the volatility $\forall t$. r_t is the performance of the financial variable I_t such as $r_t = \log\left(\frac{I_t}{I_{t-1}}\right)$.

In addition, the forecast for quarterly GDP growth is based on the direct method with several stages. For all t, the forecast H horizon makes it possible to define the following relationship, from the MIDAS-AR model at $(2n_D + 2n_M + 2)$ parameters estimated by the non-linear least-squares method – NLS, as:

$$y_{t_q+H} = \hat{\alpha}_0^{(H)} + \mu^{(H)} y_{t_q} + \sum_{i=1}^{n_D} \hat{\alpha}_i^{(H)} B(L_D; \hat{\theta}_i^{(H)}) \hat{v}_{i,t_d+\tau_1}^{(D)} + \sum_{j=1}^{n_M} \hat{\beta}_j^{(H)} B(L_M; \hat{\theta}_j^{(H)}) x_{j,t_m+\tau_2}^{(M)} \quad (5)$$

Where: $\hat{\alpha}_0^{(H)}, \hat{\alpha}_1^{(H)} \dots, \hat{\alpha}_{n_D}^{(H)}, \hat{\theta}_1^{(H)}, \dots, \hat{\theta}_{n_D}^{(H)}, \hat{\beta}_1^{(H)} \dots, \hat{\beta}_{n_M}^{(H)}, \hat{\theta}_1^{(H)}, \dots, \hat{\theta}_{n_M}^{(H)}, \mu^{(H)}$, the vector of NLS estimators.

3. DATA

The series are extracted mainly from the "FRED database" and "Datastream". These are daily, monthly and quarterly data. The quarterly data relate to the seasonally adjusted GDP growth rates, relating to the selected economies. They cover the period from 1970q1 to 2018q4 and are from the "FRED database". The economic variables are observed on a monthly frequency and noted by "ipm", "cos Index", "leadIndex", "capu" and "unemp". They are from the same source as the GDP data. The financial variables with daily frequencies relate to the commodity prices index noted "CRB index" and stock market indices of the United States "S&P 500", France "CAC 40", Great Britain "FTSE 100", Germany "DAX" and Japan "Nikkei 225". These are extracted from the "Datastream" database. [Table 1](#) describes all these data.

TABLE 1: DESCRIPTION OF DATA

Series	Frequency	Description	Period
PRICE INDEX			
cac	Daily	France. CAC 40	09juil1987-31déc2018
sp	Daily	USA. S&P 500	02jan1970-31déc2018
ft	Daily	UK. FTSE 100	04jan1988-31déc2018
dax	Daily	GER. DAX 30	04jan1988-31déc2018
nik	Daily	JP. Nikkei 225	04jan1988-31déc2018
VARIABLES			
rgdp (*)	Q	Real GDP Growth	1970q1-2018q4
ipm (*)	M	Index of Industrial Production Manufact	jan1970-dec2018
cos (*)	M	Consumer Opinion Survey Index	jan1970-dec2018
leadIndex (*)	M	Leading Indicator OCDE normalized	jan1970-dec2018
Capu (**)	M	Capacity Utilization Rate	jan1970-dec2018
unemp (*)	M	Unemployment Rate	jan1970-dec2018
COMMODITY PRICES			
crb	Daily	Commodity (CRB) BLS Spot Index	02jan1970-31dec2018

Notes: Data are observed at separate frequencies (*Q* = Quarterly; *M* = Monthly; *Daily* = Daily). The sign (*) shows that the variable is available for the five countries in the sample. The sign (**) indicates that the series is only available for the United States. For financial indices, they come from the "Datastream" database. On the other hand, the GDP and the activity indicators were extracted from "FRED Database". The observation periods are set out in the table. The stock prices indices are those of the financial markets of the USA, France, United Kingdom, Germany and Japan. The commodity prices index is an aggregate indicator of commodity prices.

4. FORECASTING RESULTS

This part of the work involves commenting on the main results from the MIDAS and MIDAS-AR forecast models for the selected countries. The Autoregressive (AR) model based on GDP growth is considered as a reference model, that is to say, a scenario of comparison with forecasts. Using the information criterion BIC has allowed validating the existence of a single lag for the AR model, regardless of the selected economy. Concerning the MIDAS models, the *crb* and stock market indices were used to measure the corresponding volatility, using an ARMA model (1.1) - GARCH (1.1). Bayes Information Criterion (BIC) determined the number of lags. The volatility profiles relating to the returns of the *cac*, *sp*, *ft*, *dax*, *nik* and *crb* index are represented by the graphs above. Outliers were treated using the "Winsorising" method at 5% of the lowest observations, of the returns of these financial indices. The volatilities resulting from the

estimation of the GARCH model are $\hat{v}_{t,cac}^{(D)}$, $\hat{v}_{t,sp}^{(D)}$, $\hat{v}_{t,ft}^{(D)}$, $\hat{v}_{t,dax}^{(D)}$, $\hat{v}_{t,nil}^{(D)}$, $\hat{v}_{t,crb}^{(D)}$, and are shown below:

The above graphs highlight a peculiarity on the period 2007-2008, corresponding to the subprime crisis. Regarding the financial markets, the corresponding volatilities all reached their highest level during this period, reflecting very high financial risks in the financial markets of New York, London, Paris, Frankfurt, and Tokyo. In addition, the volatility of the return on the S&P 500 index showed a peak in October 1987 that highlights the crashes in the financial markets (bond and equity) in the United States. These findings suggest the importance of taking into account the financial sphere when explaining the sources of economic fluctuations. Concerning the behaviour of the commodity markets which is evaluated on the basis of the volatility of the yield of the CRB index, three peaks have been relatively identified over the period 1970-2018. The first one, which dates from 1973, coincides with the first oil shock in October 1973 (nominal fall in the price of a barrel of oil) that led to the depreciation of the US dollar.

The second peak observed in 2008 relates to the financial crisis, which led to large fluctuations in the commodities prices, especially food, metals and energy. Finally, a last less significant peak was observed in 2016, following the drop in oil and metal prices. Fluctuations in volatility relative to the CRB index can also be explained by imbalances in emerging countries.

As has already been confirmed in the work of Stock & Watson (2003), Ferrara (2014), these indicators have also helped in this study to improve the explanation of fluctuations in economic activity. In fact, in applications, these volatilities were initially omitted in the process of explaining economic fluctuations. Then, the financial variables were introduced one by one in the different models. A third specification consisted of simultaneously mobilizing the monthly activity variables and daily financial information (volatilities). The objective of using this procedure is to obtain more precise forecasts and justify their ability to explain economic fluctuations.

4.1. Forecast evaluation

This section is intended to compare the models used for predicting the GDP growth. By Assessing goodness of forecasts using the mean square forecasting errors (MSFE) for each forecast horizon H . Let $H=0, 1/3, 2/3, 1, \dots, 11/3$, the forecast horizons; the different models $m= \text{AR, MIDAS and MIDAS-AR}$; k is relative to the GDP growth of country i , the MSFE is computed as:

$$MSFE_{H,m,k} = \frac{1}{T - \tau} \sum_{t=\tau}^{T-1} (\hat{y}_{t+H,m,k} - y_{t+H,k})^2, \quad (6)$$

Where T is the number of observations, τ is the initial in-sample period to computing the first forecasts, $y_{t+H,k}$ is the realized value of GDP at time $t + H$, and $\hat{y}_{t+H,m,k}$ is the model m forecast of $y_{t+H,k}$ made at time t . So the expression of RMSFE is given by:

$$RMSFE_{H,m,k} = \sqrt{\frac{1}{T - \tau} \sum_{t=\tau}^{T-1} (\hat{y}_{t+H,m,k} - y_{t+H,k})^2} \quad (7)$$

Thus, the comparison of the performance of forecasting models relates to that of RMSFE criterion. The lower the RMSFE, the better the forecasting performance of

the model. Moreover, to give a better explanation of the performance of models, comparisons of their predictive power were applied for H horizons, in accordance with the indicators (economic and/or financial) used.

4.2. Out-of-sample comparison

Regarding the performance of the models, the sample is divided into two sub-periods relating to the estimation sample⁴ and evaluation sample placing between 2007Q1 and 2018Q4. The RMSFE criterion (Root Mean Square Forecast Error relative to the Autoregressive model (Theil's Indicator) is used as the indicator of appreciation of the forecast quality. Table 2 gives the RMSFE values of each model, for the H horizons. Next, Tables 3, 4, 5, 6, 7 (Appendix A) show the performance of each forecast model. Finally, the comparisons of the RMSFEs relating to the models including the activity variables and those taking into account simultaneously the activity and financial variables, are presented in tables 8, 9, 10, 11, 12 (Appendix B)

The results (Table 2) show that the so-called "MIDAS" model was generally more efficient in terms of forecasting than the reference AR model. In fact, for the five countries, the MIDAS model performed better than the reference model even if for a few horizons, the opposite situation is observed. For example, for the case of the United States, the MIDAS model was highly efficient compared to the AR model, except for the $H = 3$ horizons; 10/3 and 11/3 for which the precision decreases considerably. The same situation seems to be observed for France, Germany and Great Britain. The case of Japan is however different because the superiority of the MIDAS model is displayed, especially for near horizons.

Concerning the MIDAS-AR models, they confirm the previously cited results, with generally sharper precision, compared to the AR reference model. Overall, both MIDAS model and MIDAS-AR model display superior performance compared to the AR Autoregressive reference model.

However, the MIDAS-AR model is more powerful in terms of forecasts than MIDAS model, especially for near horizons. This result is confirmed for all the selected

⁴ For the United States, it is the period 1970q1-2006q4. For Germany, it is the period 1970q2-2006q4. For France, the estimation period is 1980q1-2006q4. For Great Britain and Japan, the estimation period is 1970q1-2006q4.

countries and suggests that the addition of the AR component improves the predictive capacity of the MIDAS model. For a better illustration of these results, the graphs below show the RMSFE values for the forecast models for each country.

In addition, in the context of nowcasting ($H = 0$), the results show the power of the MIDAS models and in especially MIDAS-AR models, compared to the AR reference model. This is explained by the non-aggregation of data with MIDAS models and also by taking into account the lags publication of data, in the case of MIDAS-AR models.

Fig.2: RMSFE of MIDAS models for the case of the US over the period 2007q1 - 2018q4

Fig.3: RMSFE of MIDAS models for the case of France over the period 2007q1 - 2018q4

Fig.4: RMSFE of MIDAS models for the case of Germany over the period 2007q1 - 2018q4

Fig.5: RMSFE of MIDAS models for the case of UK over the period 2007q1 - 2018q4

Fig.6: RMSFE of MIDAS models for the case of Japan over the period 2007q1 - 2018q4

TABLE 2: Average relative RMSFE performance of different classes of mixed frequency models against AR benchmark

		<i>Forecast horizon (H)</i>											
	<i>Models</i>	0	1/3	2/3	1	4/3	5/3	2	7/3	8/3	3	10/3	11/3
USA	<i>Midas</i>	0.72	0.75	0.78	0.81	0.86	0.86	0.89	0.91	0.94	0.97	0.98	1.02
	<i>Midas-AR</i>	0.59	0.64	0.65	0.79	0.72	0.77	0.81	0.84	0.90	0.97	0.97	1.00
France	<i>Midas</i>	0.51	0.55	0.58	0.61	0.64	0.67	0.72	0.76	0.79	0.84	0.88	0.94
	<i>Midas-AR</i>	0.46	0.49	0.53	0.57	0.59	0.62	0.66	0.73	0.76	0.77	0.81	0.86
Allemagne	<i>Midas</i>	0.71	0.75	0.79	0.83	0.86	0.87	0.92	0.96	0.97	0.97	1.00	1.04
	<i>Midas-AR</i>	0.62	0.68	0.71	0.74	0.77	0.82	0.87	0.87	0.90	0.90	0.94	0.97
UK	<i>Midas</i>	0.53	0.55	0.62	0.66	0.67	0.67	0.72	0.75	0.79	0.84	0.88	0.88
	<i>Midas-AR</i>	0.44	0.47	0.52	0.55	0.56	0.59	0.63	0.66	0.69	0.73	0.76	0.81
Japon	<i>Midas</i>	0.60	0.62	0.65	0.79	0.76	0.78	0.83	0.87	0.90	0.95	0.96	0.99
	<i>Midas-AR</i>	0.52	0.55	0.59	0.64	0.68	0.75	0.75	0.76	0.78	0.83	0.87	0.90

Notes: The results in this table are from the assessment of the forecast of the above models, after the estimates, according to the country in question. The evaluation sample is 2007q1-2018q4. For each model, an RMSE is calculated compared to that of the reference AR model, the number of delays of which is given by the Bayesian information criterion - BIC.

Furthermore, the RMSFE of each model was also computed to have a better appreciation of these results, in accordance with the indicators used for each selected economy. The inherent results are set out in [Tables 3, 4, 5, 6, 7](#) ([Appendix A](#)) As highlighted above, the performance of the different models is measured by considering

a single economic indicator, see “Table 3” in appendix A for example for the case of the United States.

Concerning the monthly variables, the forecasts indicate that MIDAS-AR gives better results compared to the AR reference model. However, this performance is just limited to close forecast horizons ($H = 0; 1/3; 2/3; 1; 4/3; 5/3; 2$), especially for the case of the United States. As for other countries, the models produced identical results, still confirming the power of the MIDAS-AR models. For $H > 2$ horizons, the MIDAS model does not provide better performance compared to the AR model in the absence of financial variables.

Moreover, when the forecast relates to the model taking into account the two types of variables (monthly and daily), the results show that performance increasingly improves with the MIDAS AR models. The MIDAS AR models displayed the lower RMSFE compared to the MIDAS model. From tables 08 to 13 (Appendix B), we can note gradual evolutions of the RMSFE, for increasingly weak horizons reflecting the use of additional information and their relevance to explain the economic fluctuations, especially in the short-term.

5. CONCLUSION

This work has shown that financial information, generally omitted from economic forecasts, has a significant explanatory power that can improve the results of these forecasts. Through the calculated volatilities, the forecasts of the economic growth have been appreciated, in both the short term and medium term. Thus, the forecasts have focused on the growth of the GDP of five developed countries namely, the United States, France, Germany, Great Britain and Japan and based on econometric models with mixed frequencies, of the MIDAS type. These are specified using monthly variables reflecting economic activity and indicators of financial variables with daily frequency.

Thus, the performances of the MIDAS and MIDAS-AR models were analyzed over different forecast horizons, compared to an AR autoregressive reference model. Then, the reflections are focused on the ability of each model to forecast GDP growth by only considering the monthly variables and adding the financial variables for all of the selected countries.

The results initially show that by taking only economic variables (monthly) into account, the MIDAS-AR model offers better forecasting quality than the MIDAS model, especially for close horizons. Then, it was observed that incorporating financial information improves the forecasts made with the different models under different forecast horizons. It should be noted that taking into account the financial sphere allows obtaining better understanding in the context of macroeconomic forecasts.

This work led to two important results that are in line with the literature concerning the forecast of macroeconomic fluctuations, see Stock & Watson ([2003](#)), Ghysels ([2004](#), [2007](#)), Ferrara et al. ([2014](#)). The first result concerns econometric models and the second relates to economic theory on the explanation of economic fluctuations. First, the relevance of mixed frequency models has been proven compared to models based on a single frequency as the Autoregressive (AR) model used as a reference in this work. Then, the second result relating to the enrichment of economic theory enable to understand that information from the financial sphere relevant to explain macroeconomic fluctuations.

However, like Stock & Watson ([2003](#)), this work did not consider the banking market, through monetary and credit aggregates. It could then be deepened by highlighting more information from the banking sector. In addition, only a few developed economies were Selected. Other developed economies could be considered, or emerging countries, or even OCDE economies for example, given the availability of information.

Availability of data and materials

The data are extracted mainly from "FRED database" (<https://fred.stlouisfed.org/tags/series>) and "Datastream". They are of daily, monthly and quarterly data, and concern the US, France, United-Kingdom, Germany and Japan. The quarterly data relate to the seasonally adjusted GDP growth rates, relating to the economies considered. The economic indicators (noted "ipm", "cos Index", "leadIndex", "capu" and "unemp") are also extracted from FRED database. For financial information with daily frequencies, relative to the "CRB index" and stock market indices of the United States "S&P 500", France "CAC 40", Great Britain "FTSE 100", Germany "DAX" and Japan "Nikkei 225", the data are extracted from the "Datastream" database.

References

- Ahn, E., & Lee, J. (2006). Volatility relationship between stock performance and real output. *Applied Financial Economics*, 16 (11), 777–784.
- Azariadis, C. (2018). Credit Cycles and Business Cycles”. *forthcoming in St. Louis Federal Reserve Review*.
- BERNANKE, B. (1983). Nonmonetary Effects of the Financial Crisis in Propagation of the Great Depression. *American Economic Review*.
- BERNANKE., G. G. (1999). The financial accelerator in a quantitative business cycle framework. *Handbook of Macroeconomics*, ed. J. B. Taylor and M. Woodford, 1341–1393.
- Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31 (3), 307-327.
- Clements, M., & Galvão, A. (2008). Macroeconomic forecasting with mixed-frequency data. *Journal of Business Economics Statistics*, 26 (4), 546–554.
- Engle, R. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 50 (4), 987–1007.
- FAMA, E. (1985). WHAT'S DIFFERENT ABOUT BANKS ? *Journal of Monetary Economics*, 29-39, Vol. 15, n°1.
- Ferrara, Marsilli, & Ortega. (2014). Forecasting growth during the Great Recession: is financial volatility the missing ingredient? *Economic Modelling*, 36. 44–50.
- FerraraL, & Marsilli. (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.
- FORONI, C. M. (2012). A comparison of mixed frequency approaches for modelling Euro Area macroeconomic variables. *Working Paper. EUI*.
- Francq, C., & Zakoïan, J.-M. (2004). Maximum likelihood estimation of pure GARCH and ARMA-GARCH processes. *Bernoulli* 10, , 605-637.
- GERTLER, M. (1988). Financial Structure and Aggregate Economic Activity: An Overview. *Journal of Money, Credit and Banking*, 559-588, Vol. 20-3.
- Ghysels, E., Santa-clara, P., & Valkanov, R. (2004.). The MIDAS Touch: Mixed Data Sampling. *Mimeo, Chapel Hill, N.C.*
- Ghysels, E., Sinko, A., & Valkanov, R. (2007). MIDAS regressions: further results and new directions. *Economic Review*, 26 (1), 53–90.
- HAMILTON, J. (1987). Monetary Factors in the Great DEPRESSION. *Journal of Monetary Economics*, 145-169, Vol.19, n°2.
- Hamilton, J. (2003). What is an oil shock? *Journal of Econometrics*, 113 (2), 363–398.
- Hamilton, J., & Lin, G. (1996). Stock market volatility and the business cycle. *Journal of Applied Economics*, 11 (5), 573-593.

- HAUBRICH, J. (1987). Optimal Financial Structure in Exchange Economies. *Working Papers - Center for Financial Research*, 18-84.
- JERMANN, U. &. (2012). Macroeconomic Effects of Financial Shocks. *American Economic Review*, Vol. 63 (1), 238-271.
- Kilian, L. (2008). The economic effects of energy price shocks. *Journal of Economic Literature*, 46 (4), 871-909.
- Ling, & Li. ((1997)). On Fractionally Integrated Autoregressive MovingAverage Time Series Models With Conditional Heteroscedasticity. *Journal of the American Statistical Association*, 92, 1184-1194.
- Senyuz, Z., Chauvet, M., & and Yoldas, E. (2012). What does financial volatility tell us about macroeconomic fluctuations? *Working Paper 9, Federal Reserve Board*.
- STOCK, J. W. (2003). Forecasting Output and Inflation: The Role of Asset Prices. *Journal of Economic Literature* , 788-829. Vol. XLI (September 2003) .

Appendix

A. Evaluation of models with monthly economic indicators

TABLE 3: Relative RMSFE performance of Mixed-Frequency Models with different indicators against “AR benchmark” - USA

		<i>Forecast horizon (H)</i>											
	Modèle	0	1/3	2/3	1	4/3	5/3	2	7/3	8/3	3	10/3	11/3
Industrial Production	<i>Midas</i>	0.57	0.59	0.62	0.65	0.69	0.72	0.77	0.91	0.97	1.00	1.03	1.04
Index Manufacturing	<i>Midas-AR</i>	0.50	0.53	0.57	0.56	0.63	0.68	0.73	0.87	0.91	0.96	0.96	0.98
Consumer Opinion	<i>Midas</i>	0.39	0.41	0.45	0.49	0.55	0.61	0.56	0.64	0.67	0.82	1.07	1.11
Survey Index	<i>Midas-AR</i>	0.36	0.38	0.44	0.46	0.46	0.49	0.51	0.58	0.81	0.99	1.05	1.07
Leading	<i>Midas</i>	0.61	0.36	0.39	0.48	0.55	0.60	0.60	0.66	0.88	0.92	1.13	1.03
Indicateur - GDP	<i>Midas-AR</i>	0.55	0.31	0.32	0.38	0.49	0.56	0.59	0.67	0.91	0.94	0.98	1.17
Capacity	<i>Midas</i>	0.65	0.70	0.58	0.64	0.66	0.66	0.73	0.77	0.86	0.88	0.94	0.96
Utilization Rate	<i>Midas-AR</i>	0.49	0.52	0.56	0.57	0.55	0.58	0.64	0.69	0.77	0.83	0.91	1.18
Unemployment	<i>Midas</i>	0.49	0.53	0.56	0.59	0.62	0.61	0.66	0.71	0.88	0.97	1.02	1.01
Rate	<i>Midas-AR</i>	0.44	0.47	0.55	0.49	0.54	0.60	0.63	0.68	0.76	0.99	0.96	1.03

Notes: The RMSFEs are obtained first by recursively estimating each model, then calculating the corresponding mean square error (MSE), compared to the AR reference model. The lag of the reference model is given for the Bayesian information criterion - BIC. The evaluation period is from 2007q1-2018q4.

TABLE 4: Relative RMSFE performance of Mixed-Frequency Models with different indicators against “AR benchmark” - France

		<i>Forecast horizon (H)</i>											
	Modèle	0	1/3	2/3	1	4/3	5/3	2	7/3	8/3	3	10/3	11/3
Industrial Production	<i>Midas</i>	0.49	0.53	0.55	0.55	0.59	0.64	0.68	0.72	0.80	0.88	0.92	1.08
Index Manufacturing	<i>Midas-AR</i>	0.43	0.45	0.50	0.54	0.61	0.61	0.67	0.61	0.87	0.95	0.95	1.17
Consumer Opinion	<i>Midas</i>	0.63	0.68	0.70	0.74	0.79	0.84	0.87	0.86	0.90	0.90	0.93	0.98
Survey Index	<i>Midas-AR</i>	0.51	0.56	0.67	0.69	0.75	0.71	0.79	0.83	0.87	0.95	0.97	1.05
Leading	<i>Midas</i>	0.55	0.59	0.64	0.66	0.66	0.71	0.76	0.84	0.89	0.98	0.93	0.95
Indicateur	<i>Midas-AR</i>	0.49	0.56	0.53	0.55	0.59	0.64	0.71	0.78	0.95	0.96	1.04	1.08
Unemployment	<i>Midas</i>	0.53	0.49	0.51	0.52	0.56	0.59	0.66	0.67	0.74	0.79	0.86	0.91
Rate-All persons	<i>Midas-AR</i>	0.39	0.45	0.48	0.49	0.54	0.57	0.56	0.62	0.66	0.78	0.88	1.00

Notes: The RMSFEs are obtained first by recursively estimating each model, then calculating the corresponding mean square error (MSE), compared to the AR reference model. The lag of the reference model is given for the Bayesian information criterion - BIC. The evaluation period is from 2007q1-2018q4.

TABLE 5: Relative RMSFE performance of Mixed-Frequency Models with different indicators against “AR benchmark” - Germany

		<i>Forecast horizon (H)</i>											
	Modèle	0	1/3	2/3	1	4/3	5/3	2	7/3	8/3	3	10/3	11/3
Industrial Production	<i>Midas</i>	0.48	0.47	0.49	0.53	0.58	0.63	0.66	0.72	0.79	0.87	0.94	0.96
Index Manufacturing	<i>Midas-AR</i>	0.33	0.38	0.45	0.49	0.52	0.60	0.60	0.76	0.75	0.81	0.89	0.93
Consumer Opinion	<i>Midas</i>	0.47	0.49	0.53	0.58	0.64	0.68	0.73	0.73	0.76	0.80	0.85	0.90
Survey Index	<i>Midas-AR</i>	0.31	0.35	0.39	0.47	0.53	0.63	0.65	0.74	0.77	0.79	0.96	0.98
Leading	<i>Midas</i>	0.69	0.64	0.66	0.69	0.73	0.77	0.80	0.85	0.89	0.94	0.97	0.98
Indicateur	<i>Midas-AR</i>	0.42	0.46	0.51	0.55	0.55	0.61	0.63	0.69	0.77	0.80	0.83	0.86
Unemployment	<i>Midas</i>	0.72	0.69	0.71	0.73	0.77	0.81	0.88	0.86	0.89	0.89	0.95	0.96
Rate	<i>Midas-AR</i>	0.48	0.61	0.65	0.68	0.69	0.64	0.78	0.89	0.88	0.85	0.98	0.97

Notes: The RMSFEs are obtained first by recursively estimating each model, then calculating the corresponding mean square error (MSE), compared to the AR reference model. The lag of the reference model is given for the Bayesian information criterion - BIC. The evaluation period is from 2007q1-2018q4.

TABLE 6: Relative RMSFE performance of Mixed-Frequency Models with different indicators against “AR benchmark” - UK

		<i>Forecast horizon (H)</i>											
	Modèle	0	1/3	2/3	1	4/3	5/3	2	7/3	8/3	3	10/3	11/3
Industrial Production	<i>Midas</i>	0.68	0.73	0.75	0.78	0.82	0.85	0.93	0.96	0.98	1.02	1.07	1.09
Index Manufacturing	<i>Midas-AR</i>	0.49	0.53	0.55	0.67	0.74	0.79	0.83	0.86	0.92	0.98	0.99	1.04
Consumer Opinion	<i>Midas</i>	0.43	0.45	0.53	0.60	0.66	0.68	0.73	0.77	0.81	0.86	0.91	0.97
Survey Index	<i>Midas-AR</i>	0.37	0.39	0.44	0.44	0.51	0.55	0.59	0.68	0.75	0.85	0.94	1.07
Lending	<i>Midas</i>	0.58	0.61	0.67	0.72	0.76	0.80	0.86	0.88	0.88	0.95	0.97	1.05
Indicateur	<i>Midas-AR</i>	0.56	0.57	0.61	0.63	0.69	0.73	0.75	0.87	0.94	0.89	0.91	0.98
Unemployment	<i>Midas</i>	0.63	0.76	0.77	0.77	0.86	0.91	0.94	0.94	0.96	1.00	1.02	1.07
Rate	<i>Midas-AR</i>	0.46	0.49	0.57	0.62	0.66	0.66	0.74	0.79	0.87	0.94	0.98	1.02

Notes: The RMSFEs are obtained first by recursively estimating each model, then calculating the corresponding mean square error (MSE), compared to the AR reference model. The lag of the reference model is given for the Bayesian information criterion - BIC. The evaluation period is from 2007q1-2018q4.

TABLE 7: Relative RMSFE performance of Mixed-Frequency Models with different indicators against “AR benchmark” - Japan

		<i>Forecast horizon (H)</i>											
	Modèle	0	1/3	2/3	1	4/3	5/3	2	7/3	8/3	3	10/3	11/3
Industrial Production	<i>Midas</i>	0.53	0.56	0.64	0.71	0.74	0.78	0.86	0.93	0.97	1.03	1.07	1.10
Index Manufacturing	<i>Midas-AR</i>	0.36	0.37	0.49	0.55	0.61	0.67	0.76	0.83	0.88	0.96	0.96	1.05
Consumer Opinion	<i>Midas</i>	0.57	0.62	0.66	0.75	0.77	0.78	0.83	0.88	0.94	1.06	1.12	1.13
Survey Index	<i>Midas-AR</i>	0.38	0.42	0.44	0.44	0.48	0.53	0.58	0.68	0.76	0.85	0.92	0.97
Lending	<i>Midas</i>	0.54	0.55	0.58	0.64	0.68	0.71	0.71	0.83	0.85	0.97	1.06	1.06
Indicateur	<i>Midas-AR</i>	0.43	0.47	0.51	0.59	0.61	0.65	0.67	0.79	0.88	0.93	1.09	0.98
Unemployment	<i>Midas</i>	0.62	0.62	0.67	0.73	0.75	0.79	0.84	0.88	0.91	0.94	0.96	0.98
Rate	<i>Midas-AR</i>	0.38	0.44	0.58	0.58	0.64	0.69	0.78	0.89	0.92	0.98	0.94	0.99

Notes: The RMSFEs are obtained first by recursively estimating each model, then calculating the corresponding mean square error (MSE), compared to the AR reference model. The lag of the reference model is given for the Bayesian information criterion - BIC. The evaluation period is from 2007q1-2018q4.

B. Evaluation of models with monthly and daily Financial indicators

Table 8: Relative RMSFE performance of Mixed Frequency Models with Monthly and Daily Indicators against Models with monthly variables - USA

		<i>Forecast horizon (H)</i>												
Monthly	Daily	Modèle	0	1/3	2/3	1	4/3	5/3	2	7/3	8/3	3	10/3	11/3
Industrial Production Index Manufacturing	CRB + S&P500	<i>Midas</i>	0.78	0.84	0.88	0.91	0.93	0.94	0.95	1.06	1.04	1.09	1.12	1.09
	CRB + S&P500	<i>Midas-AR</i>	0.64	0.79	0.81	0.87	0.89	0.91	0.95	0.97	1.00	1.02	1.01	1.11
Consumer Opinion Survey Index	CRB + S&P500	<i>Midas</i>	0.81	0.83	0.85	0.88	0.91	0.87	0.97	0.94	1.03	1.09	1.11	1.14
	CRB + S&P500	<i>Midas-AR</i>	0.81	0.81	0.85	0.87	0.92	0.83	0.95	0.99	1.08	1.04	1.16	1.12
Leading Indicator	CRB + S&P500	<i>Midas</i>	0.86	0.87	0.88	0.85	0.88	0.81	0.85	0.91	0.99	1.01	1.08	1.11
	CRB + S&P500	<i>Midas-AR</i>	0.78	0.79	0.83	0.83	0.85	0.80	0.84	0.87	1.04	0.99	1.06	1.09
Capacity Utilization Rate	CRB + S&P500	<i>Midas</i>	0.89	0.93	0.97	0.81	0.99	0.88	0.89	0.96	1.11	1.09	1.16	1.21
	CRB + S&P500	<i>Midas-AR</i>	0.69	0.69	0.71	0.74	0.77	0.84	0.82	0.89	1.05	1.12	1.18	1.26
Unemployment Rate	CRB + S&P500	<i>Midas</i>	0.88	0.89	0.87	0.83	0.91	0.95	0.93	0.90	1.11	0.97	1.00	1.06
	CRB + S&P500	<i>Midas-AR</i>	0.83	0.85	0.91	0.80	0.87	0.93	0.93	1.04	1.06	1.04	1.07	0.97

Notes: The RMSFEs are obtained first by recursively estimating each model combining the monthly variables and financial volatilities, then calculating the mean square error (MSE) of the model, compared to the model with monthly variable only. The evaluation period is from 2007q1-2018q4.

Table 9: Relative RMSFE performance of Mixed Frequency Models with Monthly and Daily Indicators against Models with monthly variables - France

Monthly	Daily	Modèle	Forecast horizon (H)											
			0	1/3	2/3	1	4/3	5/3	2	7/3	8/3	3	10/3	11/3
Industrial Production Index Manufacturing	CRB + CAC 40	<i>Midas</i>	0.81	0.91	0.87	0.93	0.91	0.89	0.95	0.83	0.85	0.90	1.07	1.13
	CRB + CAC 40	<i>Midas-AR</i>	0.79	0.79	0.83	0.77	0.86	0.80	0.93	0.97	0.99	1.08	1.05	1.06
Consumer Opinion Survey Index	CRB + CAC 40	<i>Midas</i>	0.85	0.88	0.91	0.87	0.87	0.92	0.96	0.94	1.01	0.99	0.88	0.94
	CRB + CAC 40	<i>Midas-AR</i>	0.83	0.88	0.82	0.85	0.84	0.83	0.92	0.90	0.89	0.97	0.85	0.93
Lending Indicator	CRB + CAC 40	<i>Midas</i>	0.77	0.86	0.94	0.92	0.97	0.93	0.98	0.89	0.92	0.83	0.97	1.07
	CRB + CAC 40	<i>Midas-AR</i>	0.75	0.81	0.93	0.88	0.89	0.84	0.94	1.05	1.03	0.94	0.93	1.00
Unemployment Rate	CRB + CAC 40	<i>Midas</i>	0.88	0.82	0.89	0.83	0.87	0.86	0.93	0.90	1.06	1.01	0.91	1.06
	CRB + CAC 40	<i>Midas-AR</i>	0.83	0.79	0.87	0.80	0.89	0.81	0.89	0.85	0.96	1.11	1.09	0.97

Notes: The RMSFEs are obtained first by recursively estimating each model combining the monthly variables and financial volatilities, then calculating the mean square error (MSE) of the model, compared to the model with monthly variable only. The evaluation period is from 2007q1-2018q4.

Table 10: Relative RMSFE performance of Mixed Frequency Models with Monthly and Daily Indicators against Models with monthly variables - Germany

Monthly	Daily	Modèle	Forecast horizon (H)											
			0	1/3	2/3	1	4/3	5/3	2	7/3	8/3	3	10/3	11/3
Industrial Production Index Manufacturing	CRB + DAX 30	<i>Midas</i>	0.83	0.88	0.84	0.91	0.93	0.83	0.88	0.80	0.97	1.06	1.09	1.17
	CRB + DAX 30	<i>Midas-AR</i>	0.69	0.83	0.77	0.79	0.85	0.74	0.72	0.73	1.11	1.01	1.12	1.14
Consumer Opinion Survey Index	CRB + DAX 30	<i>Midas</i>	0.79	0.87	0.82	0.83	0.81	0.87	0.92	0.93	0.97	1.04	0.99	1.08
	CRB + DAX 30	<i>Midas-AR</i>	0.75	0.82	0.69	0.79	0.77	0.80	0.91	0.86	0.84	0.97	0.92	1.04
Lending Indicator	CRB + DAX 30	<i>Midas</i>	0.80	0.91	0.91	0.86	0.84	0.97	1.16	1.12	1.03	0.96	0.91	0.96
	CRB + DAX 30	<i>Midas-AR</i>	0.77	0.85	0.83	0.90	0.99	0.94	0.91	0.95	0.98	1.14	1.09	1.05
Unemployment Rate	CRB + DAX 30	<i>Midas</i>	0.93	0.91	0.98	0.90	0.88	0.91	0.89	0.94	1.03	1.11	1.14	0.91
	CRB + DAX 30	<i>Midas-AR</i>	0.88	0.85	0.86	0.89	0.93	0.90	0.85	0.92	0.96	1.06	1.04	1.15

Notes: The RMSFEs are obtained first by recursively estimating each model combining the monthly variables and financial volatilities, then calculating the mean square error (MSE) of the model, compared to the model with monthly variable only. The evaluation period is from 2007q1-2018q4.

Table 11: Relative RMSFE performance of Mixed Frequency Models with Monthly and Daily Indicators against Models with monthly variables - UK

Monthly	Daily	Modèle	Forecast Horizon (H)											
			0	1/3	2/3	1	4/3	5/3	2	7/3	8/3	3	10/3	11/3
Industrial Production Index Manufacturing	CRB+FTSE100	<i>Midas</i>	0.81	0.88	0.86	0.87	0.88	0.92	0.95	0.91	0.98	1.05	0.97	0.93
	CRB+FTSE100	<i>Midas-AR</i>	0.71	0.86	0.86	0.91	0.83	0.82	0.88	0.93	0.97	1.08	1.03	1.09
Consumer Opinion Survey Index	CRB+FTSE100	<i>Midas</i>	0.92	0.96	0.98	0.94	0.91	0.93	0.90	0.96	0.90	1.08	1.09	1.07
	CRB+FTSE100	<i>Midas-AR</i>	0.88	0.83	0.84	0.94	0.87	0.81	0.88	0.91	0.93	1.17	1.05	1.09
Lending Indicator	CRB+FTSE100	<i>Midas</i>	0.94	0.88	0.93	0.98	0.92	0.95	0.95	0.98	1.09	1.13	0.97	1.05
	CRB+FTSE100	<i>Midas-AR</i>	0.89	0.86	0.86	0.91	0.88	0.93	1.01	1.15	0.87	0.93	0.99	1.06
Unemployment Rate	CRB+FTSE100	<i>Midas</i>	0.90	0.93	0.98	0.93	0.97	0.96	1.04	1.06	0.87	0.89	0.94	0.91
	CRB+FTSE100	<i>Midas-AR</i>	0.85	0.84	0.87	0.89	0.85	0.86	1.14	1.01	0.83	1.08	1.12	1.09

Notes: The RMSFEs are obtained first by recursively estimating each model combining the monthly variables and financial volatilities, then calculating the mean square error (MSE) of the model, compared to the model with monthly variable only. The evaluation period is from 2007q1-2018q4.

Table 12: Relative RMSFE performance of Mixed Frequency Models with Monthly and Daily Indicators against Models with monthly variables - Japan

Monthly	Daily	Modèle	Forecast Horizon (H)											
			0	1/3	2/3	1	4/3	5/3	2	7/3	8/3	3	10/3	11/3
Industrial Production Index Manufacturing	CRB + Nikkei	<i>Midas</i>	0.88	0.86	0.85	0.93	0.95	0.99	1.01	0.94	0.91	1.02	0.88	0.90
	CRB + Nikkei	<i>Midas-AR</i>	0.82	0.80	0.85	0.88	0.86	0.93	0.91	0.97	0.89	0.87	0.84	0.88
Consumer Opinion Survey Index	CRB + Nikkei	<i>Midas</i>	0.81	0.93	0.90	0.97	0.99	0.92	0.97	0.93	0.91	0.96	1.06	1.05
	CRB + Nikkei	<i>Midas-AR</i>	0.70	0.89	0.87	0.90	0.91	0.92	0.92	0.89	0.85	1.06	1.12	0.97
Lending Indicator	CRB + Nikkei	<i>Midas</i>	0.87	0.89	0.94	0.83	0.90	1.01	0.98	1.05	0.93	1.03	1.05	0.96
	CRB + Nikkei	<i>Midas-AR</i>	0.78	0.76	0.81	0.86	0.91	0.97	0.91	1.03	0.89	1.07	1.09	0.95
Unemployment Rate	CRB + Nikkei	<i>Midas</i>	0.91	0.89	0.93	0.91	0.89	0.91	0.99	0.87	1.02	1.06	1.07	1.11
	CRB + Nikkei	<i>Midas-AR</i>	0.85	0.86	0.89	0.88	0.87	0.93	0.97	0.98	0.94	1.03	1.09	0.95

Notes : Les RMSFE sont obtenues d'abord en estimant de façon récursive chaque modèle avec et sans volatilités financières, puis de calculer l'erreur quadratique moyenne du modèle avec variables journalières par rapport au modèle à variable mensuelle uniquement. La période d'évaluation est de 2007q1-2018q4.