# DOCUMENT DE TRAVAIL

# N° 515

**NOWCASTING GLOBAL ECONOMIC GROWTH:**

**A FACTOR-AUGMENTED MIXED-FREQUENCY APPROACH**

Laurent Ferrara and Clément Marsilli

October 2014

BANQUE DE FRANCE

EUROSYSTÈME

DIRECTION GÉNÉRALE DES ÉTUDES ET DES RELATIONS INTERNATIONALES

DIRECTION GÉNÉRALE DES ÉTUDES ET DES RELATIONS INTERNATIONALES

**NOWCASTING GLOBAL ECONOMIC GROWTH:**

**A FACTOR-AUGMENTED MIXED-FREQUENCY APPROACH**

Laurent Ferrara and Clément Marsilli

October 2014

# Nowcasting global economic growth: A factor-augmented mixed-frequency approach

Laurent Ferrara* – Clément Marsilli†

We would like to thank C. Schumacher and K. Drechsel for their suggestions as well as participants to the ISF 2014 in Rotterdam for useful comments. We also would like to thank Valérie Vogel for excellent research assistance. The views expressed herein are those of the authors and do not necessarily reflect those of the Banque de France.

*Banque de France, International Macroeconomics Division, laurent.ferrara@banque-france.fr

†Banque de France, International Macroeconomics Division, clement.marsilli@banque-france.fr.

## Résumé

L'évaluation en temps réel de la croissance mondiale constitue un véritable challenge pour les économistes. Le Fond Monétaire International propose dans le cadre de son rapport bi-annuel *WEO* (*World Economic Outlook*) une mesure de PIB mondial souvent considérée comme la série temporelle annuelle de référence. Dans cet article, nous développons une approche de *nowcasting* mensuel de la croissance économique à l'échelle globale. Notre approche repose sur une modélisation multi-fréquentielle à facteurs, FA-MIDAS (Factor-Augmented MIxed DAta Sampling), permettant (i) d'exploiter les données de nombreux pays et secteurs de l'économie mondiale puis (ii) de les agréger de haute (mois) à basse (année) fréquence pour prévoir la croissance de l'année en cours. Les résultats obtenus dans un exercice de *quasi* temps réel sur la période récente montre que les projections réalisées avec notre modélisation offre un indicateur pertinent et précis de l'évolution de la croissance mondiale contemporaine.



Mots-clés – Croissance mondiale, Nowcasting, Modélisation MIDAS à facteurs.



## Abstract

Facing several economic and financial uncertainties, assessing accurately global economic conditions is a great challenge for economists. The International Monetary Fund proposes within its periodic World Economic Outlook report a measure of the global GDP annual growth, that is often considered as the benchmark nowcast by macroeconomists. In this paper, we put forward an alternative approach to provide monthly nowcasts of the annual global growth rate. Our approach builds on a Factor-Augmented MIxed DAta Sampling (FA-MIDAS) model that enables (i) to account for a large monthly database including various countries and sectors of the global economy and (ii) to nowcast a low-frequency macroeconomic variable using higher-frequency information. Pseudo real-time results show that this approach provides reliable and timely nowcasts of the world GDP annual growth on a monthly basis.



Keywords – Global growth, Nowcasting, Factor-Augmented MIDAS.

JEL Codes – C53, E37.

## Non-technical summary

The International Monetary Fund provides in its World Economic Outlook (WEO) bi-annual report global estimates that are considered by experts in the field as benchmark figures when aiming at monitoring the world economy. The IMF releases estimates of annual global growth for the past years but also for the current year (i.e. nowcasts) and the two upcoming years (i.e. forecasts). The main issue with those IMF-WEO nowcasts is that they reflect an annual growth rate and are released at a quarterly frequency, while obviously economists have at disposal a large set of information on the world economy available on a higher frequency. Against this background, when aiming at nowcasting global growth on a high frequency basis, letâĂŹs say monthly, then one faces two major issues namely (i) a data-rich environment and (ii) a discrepancy between annual GDP figures, on the one hand, and monthly information, on the other hand. In this paper, we propose a new tool to address those issues and hence to evaluate the contemporaneous global outlook in real time. Our methodology combines the Mixed Data Sampling (MIDAS) technology that enables the use of high frequency data to forecast a variable sampled at a lower frequency with the factorial analysis as a reduction dimension technique. Therefore the Factor Augmented MIDAS modeling is twofold. In a first step, we aggregate a large monthly database including 37 countries and various sectors of the global economy into a small numbers of factors that summarizes the information. Then in a second step we forecast the annual world GDP growth rate using the monthly factors within the MIDAS framework. Our nowcasting approach focuses on nowcasting the GDP growth figure of the current year from eleven months ahead, corresponding to January, up to the zero horizon, i.e. December. We evaluate our approach in an empirical exercise based on global output nowcasts of the IMF-WEO over the post-crisis period from January 2010 to December 2013. Our global growth monthly estimates of the current year are compared with those stemming from the successive releases of IMF-WEO reports. The results show that the FAMIDAS approach provides reliable and timely nowcasts of the world GDP annual growth, especially at the beginning of each year when few information about the current year is available. The monthly update of the nowcasts constitutes a pertinent indicator of the world economic activity.

# 1 Introduction and motivation

Assessing world economic growth in real-time is a key point for macroeconomists in charge of monitoring global economic issues but also a real challenge for econometricians. There is currently no global statistical institute in charge of providing official quarterly national accounts at a global level, in spite of recent efforts in this direction coordinated by international institutions. In this respect, the OECD now releases real GDP growth rate figures for the G20 aggregate on a quarterly basis, based on a common work with several other institutions, such as IMF, BIS, ECB or Eurostat, within the framework of the G20 Data Gaps Initiative[1]. This G20 GDP has the great advantage of being sampled on a quarterly basis, but presents the drawbacks of (i) starting only in 2002 which somewhat limits the econometric analysis and (ii) focusing only on G20 countries leaving aside around 15% of world GDP. In addition, GDP figures are released around 70 days after the end of the quarter.

Another well known reference among macroeconomists is the IMF that provides global estimates that are considered by experts in the field as benchmark figures when aiming at monitoring the world economy. The time series of the annual global growth, as provided by the IMF in the April 2014 World Economic Outlook (WEO hereafter), is presented in Figure 1, from 1995 to 2013.

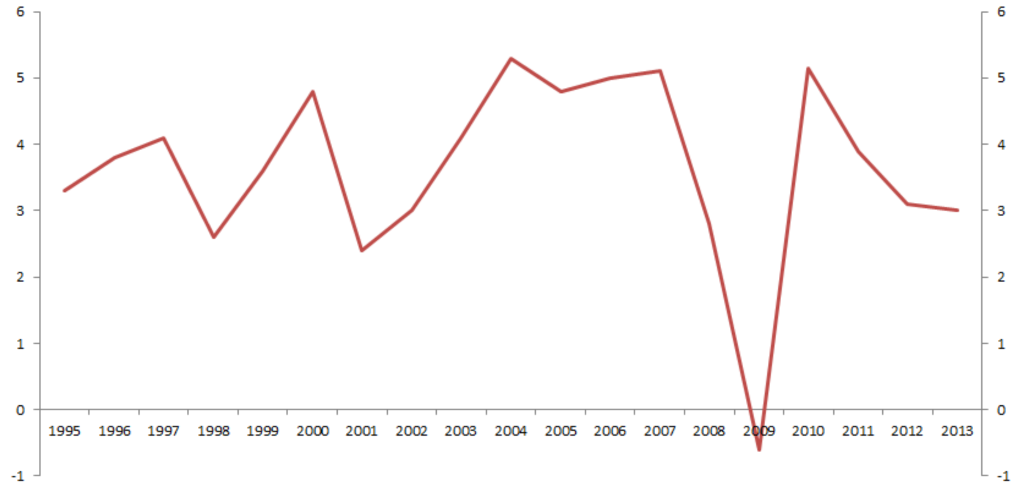


Figure 1: Annual global growth estimates (source: WEO-IMF, April 2014).

In this paper, we will consider this IMF-WEO series as the definitive estimates[2]. We clearly see that the world economic growth has been strongly affected by the Great Recession in 2009, reaching its lowest level since the start of the series. We also observe a sharp increase in growth since the early 2000s, due to some emerging countries, like China in particular. Since the bounce-back in 2010, it seems that the world economy was rather sluggish, showing a marked deceleration.

[1]For further details see OECD website.

[2]The IMF WEO estimates and projections account for 90 percent of the world purchasing-power-parity weights and are available in the IMF website.

In fact, each time the IMF-WEO is published, the IMF releases estimates of annual global growth for the past years but also for the current year (i.e. nowcasts) and the two upcoming years (i.e. forecasts). The WEO is released two times per year (usually in April and October) and two other WEO updates also come in January and July, but with much less details. Thus, it turns out that four nowcasts of the world economic growth rate for the current year are available.

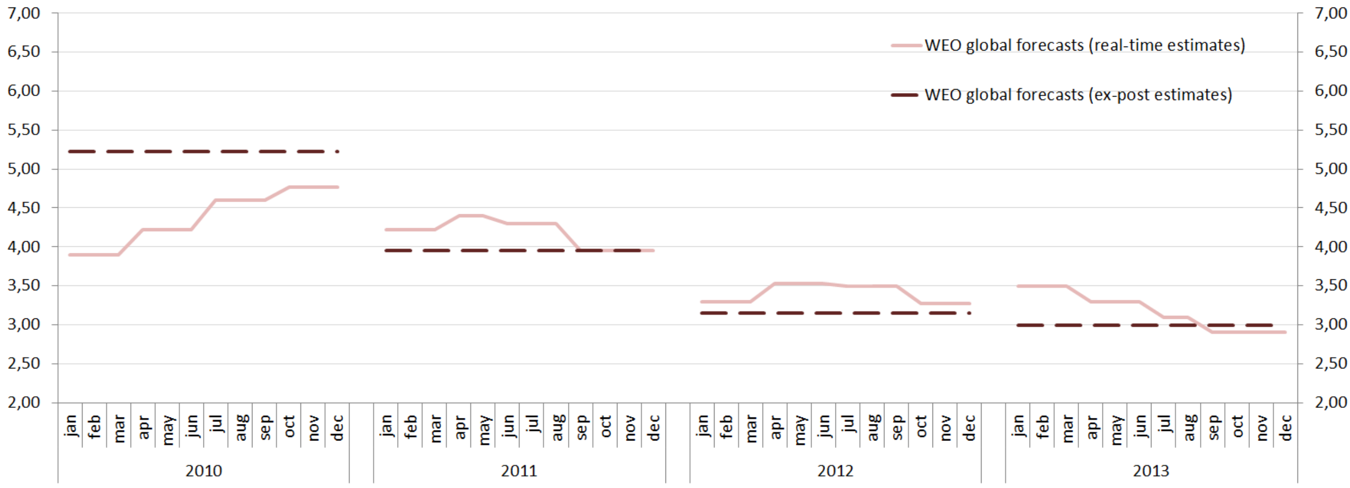


FIGURE 2: WEO Global growth nowcasts and final estimates over the sluggish recovery period, as provided in April 2014.

In Figure 2, we present the evolution of IMF-WEO nowcasts for global growth over the period 2010-2013, as well as the definitive figures stemming from the April 2014 WEO release. It is noteworthy that there a clear bias at the beginning of each year, then the nowcasts tend to slowly converge to the realized growth rate. However, this bias does not appear to be systematic. Indeed, it turns out that in 2010, the IMF started by largely underestimating global growth: while the final growth is estimated at 5.2%, the first nowcasts were slightly above 3% in the wake of the Great Recession that affected simultaneaously all the countries. Then the first revision of the year that came with the April 2010 WEO nowcast led to an upward shift by around one percentage point. In opposition, the IMF tended to overestimate growth in their nowcasts in 2011 and 2012. Those optimistic forecasts are partly related to the higher than expected fiscal multipliers, especially in the euro area in 2011 and 2012 as acknowledged by Blanchard and Leigh (2013). In fact, fiscal consolidation programs implemented in the main advanced countries strongly weighed on growth, at least much more than expected by standard macroeconomic models. In addition, it is likely that some confidence effects, often neglected in forecasting models, were at play during this specific period of time, acting as a drag on growth, especially on investment.

The main issue with those IMF-WEO nowcasts is that they reflect an annual growth rate and are released at a quarterly frequency, while obviously economists have at disposal a large set of information on the world economy available on a higher frequency. For example, for many countries, practitioners have access to a large volume of data from opinion surveys of households and businessmen as well as various series on prices (equity prices, housing prices, etc.) and real activity, such as the industrial production index (IPI), household consumption, unemployment rate, etc. Some recent papers have tackled this issue by considering various approaches. For example, Golinelli and Parigi (2013) have developed several bridge models to forecast quarterly world GDP growth rates based on monthly indicators for many countries. Rossiter (2010) takes a similar approach but only considers PMI indicators to explain global variables. Matheson (2011) estimates some dynamic factor models for a large panel of countries and then aggregates forecasts in order to get estimates of the global growth. Drechsel et al. (2014) also show that adding monthly leading global indicators (such as OECD composite leading indicators) to the IMF-WEO forecasts, through bridge equations, lead to accuracy improvements in some cases.

Against this background, when aiming at nowcasting global growth on a high frequency basis, let's say monthly, then one faces two major issues namely (i) a data-rich environment and (ii) a discrepancy between annual GDP figures, on the one hand, and monthly information, on the other hand. In recent years, those two issues have been tackled by econometricians. First, a number of econometric methods have been proposed in the literature enabling to deal with such data-rich environments. Among the different methodologies, dynamic factor models have grown significantly in popularity since the early 2000s and the seminal papers of Forni et al. (2000), Forni et al. (2003) and Stock and Watson (2002). These models can be used to summarise the information contained in large datasets into a small number of factors common to those variables and have proved very useful in macroeconomic analysis and forecasting in a data-rich environment (see among others Giannone et al. (2008)). Second, when dealing with variables sampled at various frequencies (e.g. annual GDP and monthly financial information), the mixed data sampling (MIDAS hereafter) approach put forward by Ghysels and his co-authors has led to many interesting results in macroeconomic applications (see Ghysels et al. (2007)). Especially in the forecasting framework, several empirical papers have shown the ability of financial information to predict macroeconomic fluctuations; we refer for example to Clements and Galvão (2008) or Ferrara et al. (2014) for the US of Ferrara and Marsilli (2013) for the euro area. Combining dynamic factor models and a MIDAS approach into a Factor-Augmented MIDAS (FA-MIDAS) model has been put forward by Marcellino and Schumacher (2010) when dealing with the German economy. This latter approach is convenient as the two main stylized facts, namely large databases and mixed frequencies, can be accounted for by the FA-MIDAS model.

In this paper, we implement the FA-MIDAS approach in order to nowcast the global GDP growth rate on a monthly basis, starting from a large database of macroeconomic indicators for several advanced and emerging countries. We compare our results with IMF-WEO nowcasts during the recovery from the Great Recession and we empirically show that our approach is able to better reflect global economic conditions, by reducing mean squared-errors, at least at the beginning of each year, when fewer information is available.

## 2 The econometric framework

The econometric methodology implemented in this paper builds on the FA-MIDAS approach put forward by Marcellino and Schumacher (2010). In this approach, the information contained in the large database of monthly macro-variables is summarized into few underlying factors, supposed to represent the common evolution of all the series. Then we assume that the annual world GDP growth rate can be explained by a MIDAS regression enabling to explain this low frequency variable by exogenous monthly variables, without any aggregation procedure and within a parsimonious framework.

To exploit a large database including various variables for different countries of the world economy, we implement first a factor analysis that reduces the dimension of the problem. Thus, assume the $1 \times n$ time vector of monthly macroeconomic variables, $X_\tau$, can be represented as the sum of two mutually orthogonal unobservable components: the common component $\chi_\tau$ and the idiosyncratic component $\xi_\tau$. For a given month $\tau$, the static factor model is defined by

$$X_\tau = \Lambda f_\tau + \xi_\tau, \tag{1}$$

where $X_\tau = (x_{\tau 1} \, \ldots \, x_{\tau n})'$ has zero mean and covariance matrix $\Gamma(0)$, $\Lambda$ is the loading matrix such that $\Lambda = (\lambda_1 \, \ldots \, \lambda_n)'$, the common components $\chi_\tau = \Lambda f_\tau$ are driven by a small number $r$ of factors $f_\tau$ common to all the variables in the model such that $f_\tau = (f_{\tau 1} \, \ldots \, f_{\tau r})'$, and $\xi_\tau = (\xi_{\tau 1} \, \ldots \, \xi_{\tau n})'$ is a vector of $n$ idiosyncratic mutually uncorrelated components, driven by variable-specific shocks.

Once the $r$ common monthly factors from the original database have been extracted, we relate them to the annual global growth $y_t$ sampled on a yearly frequency described by the index $t$. Thus, we observe $\mathsf{m}$ times the explanatory factor over the period $[t-1, t]$ which corresponds to $[\tau/\mathsf{m} - 1, \tau/\mathsf{m}]$ where $\mathsf{m} = 12$. The standard multivariate MIDAS regression for explaining a stationary low-frequency variable $y_t$, augmented with a first order autoregressive component, is given by:

$$y_t = \beta_0 + \sum_{i=1}^{r} \beta_i \; m_K(\theta_i, L) \, \hat{f}_{i,t}^{(\mathsf{m})} + \lambda y_{t-1} + \varepsilon_t, \tag{2}$$

where $f_{i,t}^{(\mathsf{m})} = f_{i,\tau}$ is one of the exogenous stationary common factor sampled at a monthly frequency. The MIDAS function $m_K(\theta, L)$ controls the polynomial weights that allows the frequency mixing. Indeed, the MIDAS specification consists in smoothing the $K$ past values of $f_t^{(\mathsf{m})}$ on which the regression is based. As in Ghysels et al. (2002), we implement the one parameter Beta lag polynomial such as

$$m_K(\theta, L) = \sum_{k=1}^{K} \frac{\theta k (1-k)^{\theta - 1}}{\sum_{l=1}^{K} \theta l (1-l)^{\theta-1}} L^{(k-1)} \tag{3}$$

where $L$ is the lag operator applied on the high frequency variable $x_t^{(\mathsf{m})}$ such that $L^s x_t^{(\mathsf{m})} = x_{\tau - s}$. In our setup we assume that the annual global growth is only influenced by the information conveyed by the last $K = 15$ values of the monthly factor $f_t^{(\mathsf{m})}$; the windows size $K$ being exogenous. It can also be noticed that the parameter $\theta$ is part of the estimation problem. Other parameterizations of the weight function can be used, but we choose (3) since it constitutes a parsimonious and reasonable restriction for which the weights are always positive.

Parameter estimation of this model described by equations (1) and (2) is carried in two steps. First, factors $f_t$ are estimated using the static principal component analysis (see Stock and Watson, 2002). An eigenvalue decomposition of the estimated covariance matrix $\widehat{\Gamma}_0 = T^{-1}\sum_{t=1}^{T} X_t X_t'$ provides the $n \times r$ eigenvector matrix $\hat{S} = (\hat{S}_1 \dots \hat{S}_r)$ containing the eigenvectors $\hat{S}_i$ corresponding to the $r$ largest eigenvalues for $i = 1, \dots, r$. The factor estimates are the first $r$ principal components of $X_t$ defined as $\hat{f}_t = \hat{S}' X_t$. Then, the MIDAS equation is estimated using standard non-linear least squares, assuming factors are known.

A tricky question arising within this kind of framework is related to the number of factors $r$ to include in the equation (2). Several statistical tests are available in the econometric literature. In the forecasting framework, it turns out that some of them lead to more accurate forecasts, as shown in Barhoumi et al. (2013). Alessi et al. (2010) have suggested an information criterion based on Bai and Ng (2002) to determine the number of factors $r$ in the context of an static factor analysis. This criterion can be written as:

$$\mathrm{IC}_p^T(r) = \log V(r, f) + c.r.p(n, T), \tag{4}$$

where $p(\cdot)$ is a penalty function defined as: $p(n,T) = \frac{n+T}{nT} \log \frac{nT}{n+T}$, and $V(\cdot)$ is a goodness-of-fit measurement based on sum of squared errors such as:

$$V(r, f) = (nT)^{-1} \sum_{t=1}^{T} \sum_{i=1}^{n} \left( X_t - \Lambda \hat{f}_t \right)^2 \tag{5}$$

which depends on the estimates of the static factors and on the number $r$ of those factors. Following Alessi et al. (2010) and according to our modelling specifications, we set the exogenous parameters $c = 2$ and $r_{max} = 5$. The estimated number of factors $r^*$ is defined as the one that minimises the criterium (4), as follows:

$$r^* = \underset{0 \le r \le r_{max}}{\arg\min}\ \mathrm{IC}_p^T(r). \tag{6}$$

The selected number of factors are therefore empirically used in (7) for global growth nowcasting purposes. The monthly nowcast of the annual global growth $\hat{y}_{t+1|t+1-h}$ is defined as the conditional expectation of $y_t$ at a given month of the current year. For all forecasting horizon $h < \mathsf{m}$, the nowcasting estimate is computed using the following Factor-Augmented MIDAS equation:

$$\hat{y}_{t+1|t+1-h}(h) = \hat{\beta}_0(h) + \sum_{i=1}^{r^*} \hat{\beta}_i(h)\ m_K(\hat{\theta}_i(h), L)\ \hat{f}_{i,t+1-h}^{(\mathsf{m})} + \hat{\lambda}(h) y_t \tag{7}$$

where $h$ is the forecasting horizon expressed in terms of the high frequency ranging from $h = 0$ months (corresponding to December) to $h = 11$ months (for January's forecasts). The equation (7) characterizes predictions of the current period involving new intermediary data of the explanatory variables using an update of the factors estimation $\hat{f}_{i,t+h}^{(\mathsf{m})}$. Besides that, the MIDAS parameters also are re-estimated at each horizon $h$ via the non-linear least squares method. It is noteworthy that we allow parameters to depend on the forecasting horizon $h$.

# 3 Empirical Results

Our methodology is based on a large data set gathering economic indicators from 37 countries, both advanced and emerging. The exhaustive list is enumerated is the appendix. We can notice that the share of those countries is more than 80% of the world GDP as computed by the IMF WEO. From those 37 economies, we choose monthly variables suppose to convey useful information to assess short-term fluctuations of economic activity. Thus for each country we select a set of real variables (industrial production, household consumption, retail sales, new car registrations, etc.), financial variables (exchange rate, stock market indexes, interest rates, etc.) and household confidence index. The variable table is also given in the appendix. Constraints are imposed on this choice, in the sense that we aim at having a similar set for each country and that we want to start our analysis in the early nineties. In addition, we augment this database using global indicators of trade, commodity prices, financial uncertainty, ... Overall we get a sample of $n = 392$ monthly variables. This database possesses the great advantage of being rapidly updated. All series are monthly and are expressed in difference or log-difference; the financial ones are sampled as the monthly average of daily quotes, and transformed in log-returns. The problem of ragged-edge series and unbalanced database is solved here by using the last available data as the contemporaneous one. This approach is referred to as the *realignement strategy* in the empirical litterature (see, for example, Marcellino and Schumacher, 2010).

Using principal component analysis defined in equation (1), we extract one monthly factor that describes variability of the whole dataset. The various implemented tests on the number of factors to select led us to choose $r = 1$. The estimated factor is displayed and compared to yearly global growth WEO estimates in Figure 3. It is noteworthy that this first factor seems to follow quite closely global growth fluctuations, in spite of some deviations during specific periods of time. The idea is now to formally relate this estimated factor to the global growth through the MIDAS equation (2). The targeted variable is the world GDP growth rate provided by the IMF in its April 2014 WEO and presented in Figure 1.

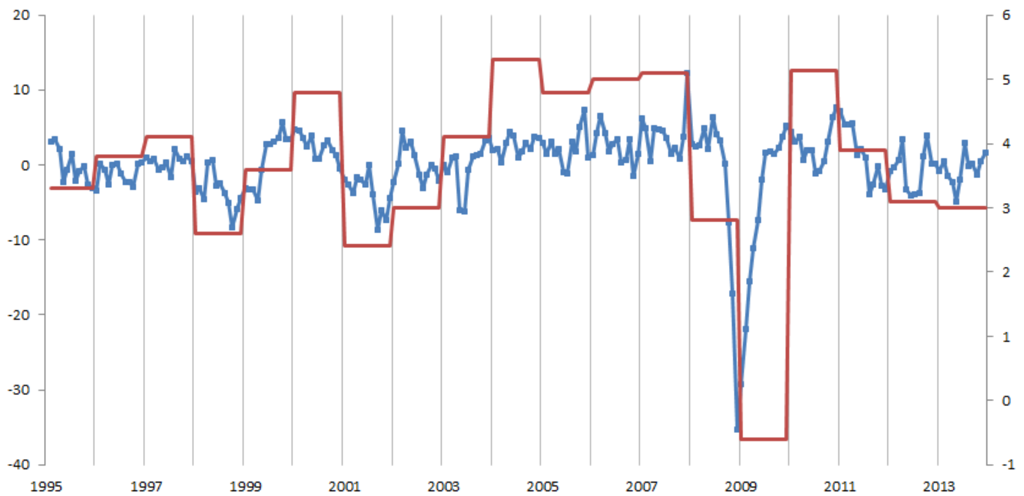


Figure 3: Explanatory factor vs. WEO Global growth estimates.

In a first step, we carry out an in-sample analysis over the period from January 1995 to December 2009. Knowing that financial data are available the last working day of the month, we suppose that nowcasts for a given month are computed at the end of each month, for 12 horizons ranging from $h = 0$ (nowcasts computed the last month of the reference year) to $h = 11$ (nowcasts computed 11 months before the end of the reference year). For each date $t$, the MIDAS regression optimally exploits the monthly fluctuations of the last $K = 15$ data of the $f_t^{(\mathrm{m})}$ series using the weight polynomial, given in equation (3). Estimated weights are presented in Figure 4. The shape of the weights is in line with what we could expect according to the forecasting horizon. Indeed for long horizons, the shape gives a non-null value to all the weights until $K = 15$. When the horizon shorten (e.g. for $h = 6$), the shape is more peaked and the maximum value is reached for $k = 2$. Finally when $h = 0$, that is when the nowcast is made in December of the current year, the mass is mainly concentrated in $k = 0$ and the function rapidly decreases.

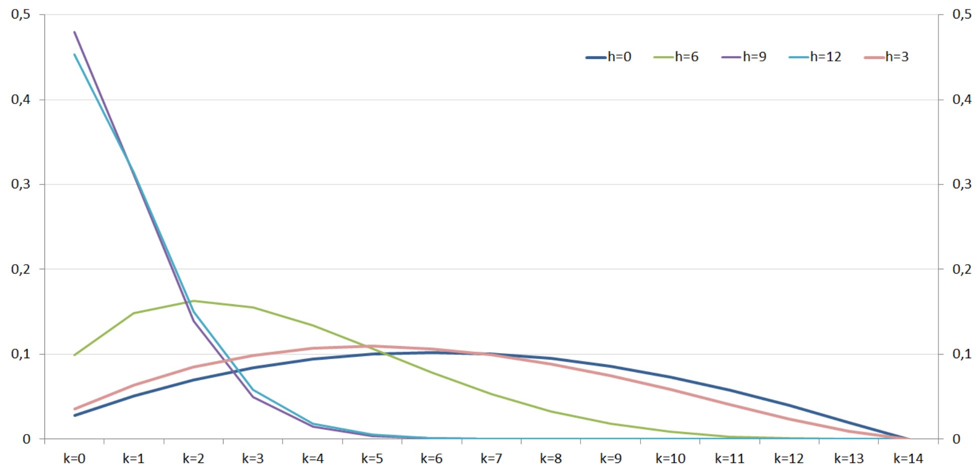


FIGURE 4: In-sample MIDAS weight functions with respect to the forecasting horizon $h$

In a second step, we implement a quasi-real-time experience over the post-crisis period from January 2010 to December 2013. For each month, we estimate the global growth of the current year and we compare it with the real-time estimates stemming from the four IMF-WEO reports released per year. In practice, we do not re-estimate all the parameters each month, but instead we use the parameters estimated using the information until December of the previous year. Empirical results are presented in Figure 5, as well as final estimates as released with the April 2014 IMF-WEO. As expected, real-time estimates tend to convergence to the final figures, which is consistent with the fact that more information leads to more accurate estimates. Our estimate evolves with the monthly flow of conjunctural information that we received within the year, while the IMF-WEO estimates is more related to the release of quarterly national accounts. We note that in 2010, the IMF-WEO largely underevaluated the bounce-back in world GDP growth, especially at the beginning of the year, while our nowcast fluctuated around the final figure. We also note that since 2011, both estimates were generally revised in the same direction.

In addition to nowcasts, we also develop non-parametric bootstrapping technique *a la* Efron (1979) in the MIDAS regression context to get confidence intervals around nowcasts and

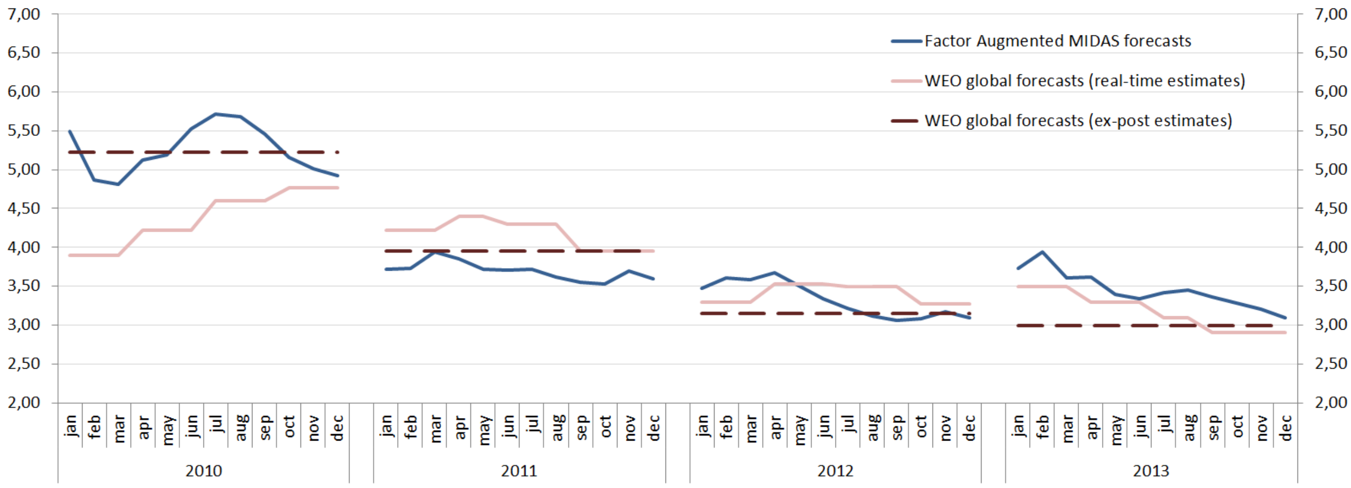


FIGURE 5: WEO vs FAMIDAS nowcasts over the period 2010-2013

hence a measure of the uncertainty. The methodology involves random resampling, with replacement, of elements from the original data to generate a replicate data vector of similar size. This kind of approach has been already used by Aastveit et al. (2014) for density forecasts and by Clements and Galvão (2008) for significance tests. The 90% confidence intervals are exhibited in Figure 6. Eyeballing the figure suggests that the uncertainty was shifted downward since the year 2010 and seems to remain broadly constant. But some periods of time present larger confidence intervals, sometimes with an asymmetry pointing out that risks are tilted to the downside (or to the upside).

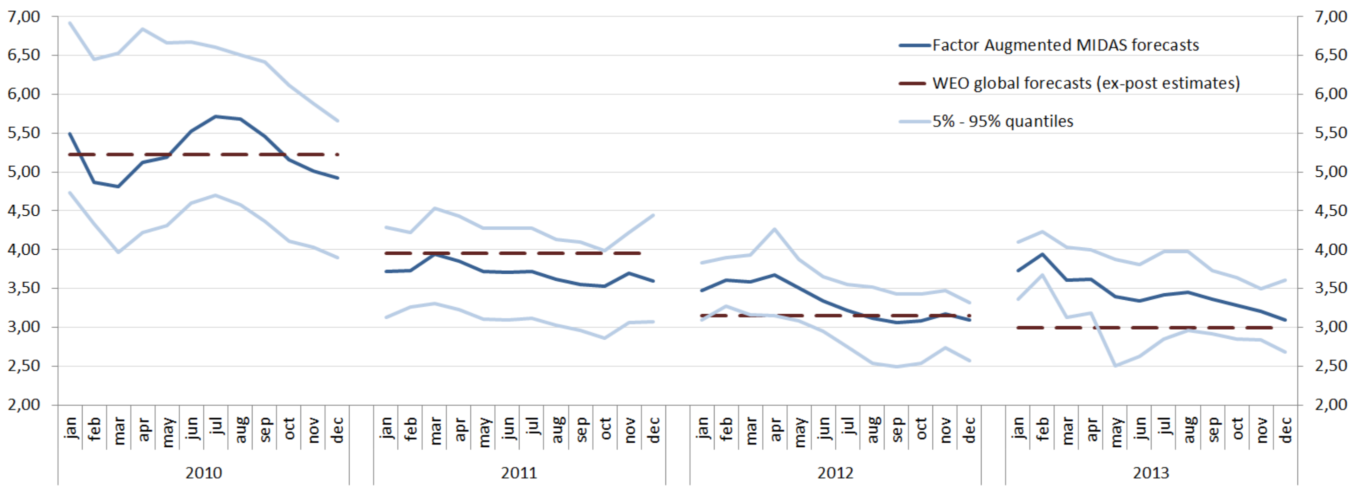


FIGURE 6: FAMIDAS nowcasts with confidence interval (5%-95%) over the period 2010-2013

In order to evaluate the accuracy of our approach, we compute the squared errors of the nowcasts stemming from both the WEO and the FA-MIDAS model. Monthly averages of squared errors over the period 2010-2013 are showed in Figure 7. Overall, the FA-MIDAS model provides more accurate nowcasts over the year and are equivalent to the WEO forecasts by the end of the year, from October to December. In fact, we notice that the forecasting gain obtained by using the FA-MIDAS is particularly important from 12 to 4 months ahead, that is from January to September. Indeed, at the the beginning of the year, the information available to the WEO update of January is rather scarce. Also, when economists are working on the preparation of the April WEO, they do not have at hand the realized GDP for the first quarter of the current year. Similarly, the release of the second quarter of GDP growth occurs well after the July update. Consequently, it seems that our tool could consitute a nice complement to the WEO estimates for economists interested in monitoring the world economic growth.

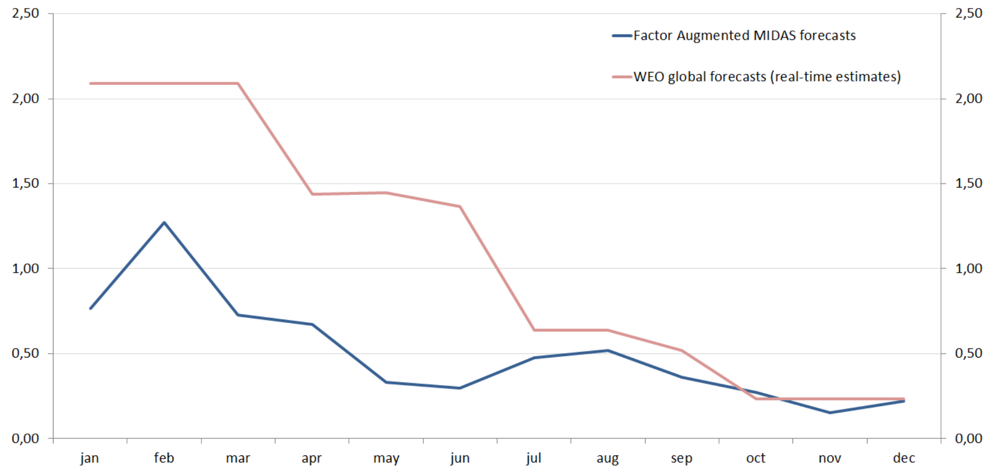


Figure 7: Monthly averages of Mean Square Errors of WEO and FA-MIDAS nowcasts

## 4 Conclusion

In this paper, we put forward a new tool in order to nowcast the global economic growth in real-time. We implement a Factor Augmented MIDAS approach enabling to explain the annual global growth by a large database of monthly variables. The targeted variable is the annual global growth estimated by the IMF in its World Economic Outlook assessment. It turns out that our tool is able to efficiently track on a high frequency the global growth. Especially nowcasts are much more accurate at the beginning of the year when fewer information is available. This tool could be fruitfully used by macroeconomists to monitor global economic developments, in addition to the IMF-WEO estimates.

## REFERENCES

Aastveit, K. A., Claudia Foroni, C., and Ravazzolo, F. (2014). Density forecasts with MIDAS models.

Alessi, L., Barigozzi, M., and Capasso, M. (2010). Improved penalization for determining the number of factors in approximate factor models. *Statistics & Probability Letters*, 80(23-24):1806–1813.

Bai, J. and Ng, S. (2002). Determining the Number of Factors in Approximate Factor Models. *Econometrica*, 70(1):191–221.

Barhoumi, K., Darné, O., and Ferrara, L. (2013). Testing the Number of Factors: An Empirical Assessment for a Forecasting Purpose. *Oxford Bulletin of Economics and Statistics*, 75(1):64–79.

Blanchard, O. J. and Leigh, D. (2013). Growth Forecast Errors and Fiscal Multipliers. *IMF Working Papers*.

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

Drechsel, K., Giesen, S., and Lindner, A. (2014). Outperforming IMF Forecasts by the Use of Leading Indicators. IWH Discussion Papers 4, Halle Institute for Economic Research.

Efron, B. (1979). Bootstrap Methods: Another Look at the Jackknife. *The Annals of Statistics*, 7(1):1–26.

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.

Ferrara, L., Marsilli, C., and Ortega, J.-P. (2014). Forecasting growth during the Great Recession: is financial volatility the missing ingredient? *Economic Modelling*, 36:44–50.

Forni, M., Hallin, M., Lippi, M., and Reichlin, L. (2000). The Generalized Dynamic-Factor Model: Identification And Estimation. *The Review of Economics and Statistics*, 82(4):540–554.

Forni, M., Hallin, M., Lippi, M., and Reichlin, L. (2003). Do financial variables help forecasting inflation and real activity in the euro area? *Journal of Monetary Economics*, 50(6):1243–1255.

Ghysels, E., Santa-clara, P., and Valkanov, R. (2002). The MIDAS Touch: Mixed Data Sampling Regression Models.

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.

Golinelli, R. and Parigi, G. (2013). Tracking world trade and GDP in real time. Temi di discussione (Economic working papers) 920, Bank of Italy, Economic Research and International Relations Area.

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.

Matheson, T. (2011). New Indicators for Tracking Growth in Real Time. IMF Working Papers 11/43, International Monetary Fund.

Rossiter, J. (2010). Nowcasting the Global Economy. Discussion Paper 12, Bank of Canada.

Stock, J. H. and Watson, M. W. (2002). Forecasting Using Principal Components From a Large Number of Predictors. *Journal of the American Statistical Association*, 97:1167–1179.

# A Database

List of the 37 countries:

– Advanced economies: France, Germany, Italia, Spain, Netherlands, United Kingdom, United States, Japan, Canada, Sweden, Switzerland, Norway, Denmark.

– Emerging Asia: China, India, Indonesia, South Korea, Taiwan, Thailand, Hong Kong, Malaysia, Singapore.

– Latin America: Brazil, Argentina, Mexico, Colombia.

– Europe: Poland, Czech Republic, Romania, Hungary, Latvia, Lituania, Bulgaria.

– Rest of the world: Russia, Turkey, South Africa, Saudi Arabia.

List of economic variables:

– Real economic conditions: Housing, Car registrations, Retail sales, Employment, Industrial production index, Unemployment rate, Producer price index, Consumer price index.

– Financial Series: Exchange rate, Money supply M2, Main national stock market index, 10 years government bond interest rate, 3 months interbank interest rate.

– Survey: Household confidence index.

– Overall indicators: Oil price (Brent, WTI and Dubai), Baltic dry index, Import and export price (CPB), Energy price (HWWI), VIX index (CBOE).

**Documents de Travail**

500. L. Behaghel, D. Blanche, and M. Roger, "Retirement, early retirement and disability: explaining labor force participation after 55 in France," July 2014

501. D. Siena, "The European Monetary Union and Imbalances: Is it an Anticipation Story?," July 2014

502. E. Mengus, "International Bailouts: Why Did Banks' Collective Bet Lead Europe to Rescue Greece?," August 2014

503. J. Baron and J. Schmidt, "Technological Standardization, Endogenous Productivity and Transitory Dynamics," August 2014

504. L. Arrondel, L. Bartiloro, P. Fessler, P. Lindner, T. Y. Mathä, C. Rampazzi, F. Savignac, T. Schmidt, M. Schürz and P.Vermeulen, "How do households allocate their assets? Stylised facts from the Eurosystem Household Finance and Consumption Survey," August 2014

505. Y. Kalantzis, "Financial fragility in small open economies: firm balance sheets and the sectoral structure," August 2014

506. V. Bignon and R. Dutu, "Coin assaying and commodity money," August 2014

507. A. Pizzo, "The Shimer puzzle(s) in New Keynesian framework," September 2014

508. F. Langot, L. Patureau and T. Sopraseuth, "Fiscal Devaluation and Structural Gaps," September 2014

509. G. Gaballo, "Sequential Coordination, Higher-Order Belief Dynamics and E-Stability Principle," October 2014

510. G. Bazot, M. D. Bordo and E. Monnet, "The Price of Stability. The balance sheet policy of the Banque de France and the Gold Standard (1880-1914) ," October 2014

511. K. Istrefi and A. Piloiu, "Economic Policy Uncertainty and Inflation Expectations," October 2014

512. C. Jardet and A. Monks, "Euro Area monetary policy shocks: impact on financial asset prices during the crisis?," October 2014

513. J. Dugast and T. Foucault, "False News, Informational Efficiency, and Price Reversals," October 2014

514. G. Cette, J. Lopez and J. Mairesse, "Product and Labor Market Regulations, Production Prices, Wages and Productivity," October 2014

515. L. Ferrara and C. Marsilli, "Nowcasting global economic growth: A factor-augmented mixed-frequency approach," October 2014

516. F. Langot and M. Lemoine, "Strategic fiscal revaluation or devaluation: why does the labor wedge matter? ," October 2014

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