Nowcasting world GDP growth with high-frequency data

Caroline Jardet, Baptiste Meunier

Nowcasting world GDP growth with high-frequency data

Caroline Jardet[1] and Baptiste Meunier[2]

Abstract:

While the Covid-19 crisis has shown how high-frequency data can help tracking the economy in real-time, we investigate whether it can improve the nowcasting accuracy of world GDP growth. To this end, we build a large dataset of 718 monthly and 255 weekly series. Our approach builds on a Factor-Augmented MIxed DAta Sampling (FA-MIDAS) which we extend with a pre-selection of variables. We find that this pre-selection markedly enhances performances. This approach also outperforms a LASSO-MIDAS – another technique for dimension reduction in a mixed-frequency setting. While we find that a FA-MIDAS with weekly data outperform other models relying on monthly or quarterly data, we also point to asymmetries. Models with weekly data have indeed performances similar to other models during "normal" times but can strongly outperform them during "crisis" episodes, above all the Covid-19 period. Finally, we build a nowcasting model for world GDP annual growth incorporating weekly data which give timely (one per week) and accurate forecasts (close to IMF and OECD projections but with 1-3 months lead). Policy-wise, this can provide an alternative benchmark for world GDP growth during crisis episodes when sudden swings in the economy make usual benchmark projections (IMF's or OECD's) quickly outdated.

Keywords: Nowcasting, mixed frequency, high frequency, large factor models, variable selection, big data

JEL classification: C53, C55, E37

(1) Banque de France, caroline.jardet@banque-france.fr
(2) European Central Bank, Aix Marseille Université, CNRS, AMSE, Marseille, France, baptiste.meunier@ecb.europa.eu

We are grateful to Laurent Ferrara and Clément Marsilli for their seminal nowcasting of world GDP, Claudia Braz, Franziska Ohnsorge, Sebastian Barnes, Matteo Mogliani, Sebastien Laurent, Ewen Gallic, Jean-Charles Bricongne, two anonymous referees, as well as participants to the Sept. 2020 BdF-PSE meeting, Oct. 2020 ECB workshop on high-frequency data, Nov. 2020 4NCBs and GEM meetings, and to our DGSEI internal seminar for useful comments. We thank Aude Le Métayer and Fabien Lebreton for excellent research assistance. The data that support the findings of this study are available from Datastream and ECB. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors with the permission of Datastream and ECB. The views expressed in this paper are those of the authors, and not those of the Banque de France, AMSE or European Central Bank. This work was supported by the French National Research Agency Grant ANR-17-EURE-0020, and by the Excellence Initiative of Aix-Marseille University - A*MIDEX.

Introduction

The sudden shock of the Covid-19 crisis – with some economies shutting down almost entirely in a matter of days – has put new emphasis on high-frequency data (Bricongne *et al.*, 2020). Weekly, daily, or even hourly data have been extensively used to assess in real-time the impact of the Great Lockdown. A number of innovative dataset have emerged: for example real-time marine traffic was used to track world trade (Cerdeiro *et al.*, 2020), hourly electricity consumption to estimate the loss of industrial activity in Europe (Chen *et al.*, 2020), daily credit card spending to quantify the consumption shock (Carvalho *et al.*, 2020), or weekly labour market statistics to model changes in US employment (Coibion *et al.*, 2020).

In the meantime, world GDP forecasts provided by international organizations such as the OECD or the IMF – widely used by economists as "benchmark" projections – have appeared to be lagging behind. These institutions assembled scenarios and released projections, but which could only be updated every two or three months, making them rapidly outdated given large and sudden changes in economic conditions. Thus, OECD projections as of March 2020 still assumed a positive figure (+2.4%) for world GDP growth in 2020. Two weeks later when most Western countries entered a strict lockdown, this scenario was already outdated. Mid-April, IMF's WEO projected world GDP at -2.9% for 2020. Forecasts were then not updated before mid-June, where they stood at -6.0% (OECD) and -4.9% (IMF). Most macroeconomists – "projections-takers" – were then facing a lack of "benchmark" projection for world GDP as those of usual "projection-issuers" (IMF and OECD) became quickly obsolete.

The purpose of this paper is to assess if high-frequency data can enhance the nowcasting of world GDP growth and therefore provide a timely alternative "benchmark" projection. To that aim, we build a large dataset of 718 monthly and 255 weekly indicators. Our approach builds on the Factor-Augmented MIxed DAta Sampling (FA-MIDAS) proposed by Marcellino and Schumacher (2010) which consists in using a principal component analysis to extract the common trends from large datasets (here one monthly and one weekly) and in running a MIDAS regression using the extracted factors. This set-up suits since: *(i)* we mix multiple frequencies when forecasting annual/quarterly world GDP growth with monthly and weekly series; and *(ii)* we rely on the aggregation of multiple national variables to make up for the lack of global variables.

We extend the FA-MIDAS approach with a pre-selection of variables. This pre-selection step aims at identifying variables that are the more informative to forecast the target variable – in our case world GDP growth. Principal components are then extracted from the selected subset of variables. Literature has shown that this pre-selection improves the forecasting accuracy of factor models – see Boivin and Ng (2006) or Bair *et al.* (2006)'s "supervised PCA". Following Bai and Ng (2008), we adopt a soft thresholding procedure under which only the top ranked predictors are kept. We consider three alternative techniques based on: the correlation between the target variable and each predictor (sure independence screening of Fan and Lv, 2008), the t-statistic associated with the coefficient in the univariate regression of the target variable on each predictor (similar to Jurado *et al.*, 2015), and LARS ordering (Bai and Ng, 2008). We also compare the performances of this approach with the sparse-group LASSO-MIDAS (Babii *et al.*, 2021), another dimension reduction technique for mixed-frequency data.

Comparing across different specifications for the FA-MIDAS, we find evidence that high-frequency data can significantly improve nowcasting performances, but only during very specific "crisis" episodes. Models with weekly data indeed show greater predictive accuracy compared with an AR model during "crisis" episodes – but have similar performances during "normal" periods. This is in line with the literature pointing out asymmetries in forecasting performance across expansions and recessions, e.g. Chauvet and Potter (2013) or Siliverstovs and Wochner (2021) who test a wide range of specifications and find that such asymmetries in forecasting performance across the business cycle phases are rather common. Our results notably confirm Siliverstovs (2021) showing that while the New York FED's nowcasting models are at least as good as an AR model during expansions, they entail substantial gains in accuracy during recessions. In our paper, we show that the predictive accuracy for models with weekly data is largely greater during the Covid-19 crisis than for models relying solely on monthly data , but that both exhibit similar performances in other periods: "normal" times and also the Great Financial Crisis.

These findings contribute to the on-going debate on whether high-frequency data enhance forecasting performances. Ferrara *et al.* (2020) showed that a nowcasting model based on high-frequency data produced more accurate forecasts for US growth as of end-March 2020 in Q1 than models based on standard macroeconomic information, but on the other hand, the INSEE (2020) find no significant accuracy gains when including high-frequency data. Our paper shows that while the timely signal provided by weekly data allows for substantial accuracy gains when the activity experiences dramatic swings, its contribution is only of second order when economic conditions are stable. It should be kept in mind that these findings are obtained in a strict data-driven procedure – with no intervention of the forecaster in the selection of series – and in a set-up very close to real-time, with the entire nowcasting framework (pre-selection, factors, MIDAS model) re-estimated and re-calibrated at each date.

As regards variable selection, we find that pre-selecting fewer but more targeted predictors markedly enhances the forecasting performances of the FA-MIDAS – in line with Boivin and Ng (2006), Bai and Ng (2008), and Schumacher (2010) among others. Upon testing different techniques, we find that the LARS technique yields more substantially gains. This extends the literature on the FA-MIDAS by adding a variable pre-selection, showing also that this step yields significant accuracy gains when using a high-dimensional dataset. More broadly, we contribute to the literature on forecasting in a mixed-frequency set-up by comparing a FA-MIDAS with the LASSO-MIDAS, respectively a dense and a sparse approach for dimension reduction. Our results show that the FA-MIDAS outperforms the latter, even more when the FA-MIDAS is combined with variable pre-selection. This might appear in line with Giannone *et al.* (2021) that showed that sparse modelling is outperformed by dense modelling when the data generating process is not of very low dimension.

Finally, we build a model using weekly data to nowcast the annual growth of world GDP. A pseudo-real-time exercise during the Covid-19 crisis shows that this model provides timely estimates with a 1-3 months lead on IMF and OECD releases. It might therefore serve as an alternative "benchmark" during "crisis" episodes when institutional projections are rapidly outdated. This extends the literature on forecasting world GDP. In this strand, some papers have used bridge models (e.g. Golinelli and Parigi, 2014), but our paper is closer to those based on large datasets such as Matheson (2011) or Ferrara and Marsilli (2019). The two main additions to this literature, in particular to the latter paper, relate to the inclusion of weekly data – shown to significantly increase performances during "crisis" episodes – and of variable pre-selection – shown to also yield significant gains in predictive accuracy.

The rest of paper is organised as follows: section 1 presents the data and statistical issues, section 2 presents the FA-MIDAS extended with pre-selection, section 3 details the strategy to compare models in a real-time set-up, and section 4 discusses results.

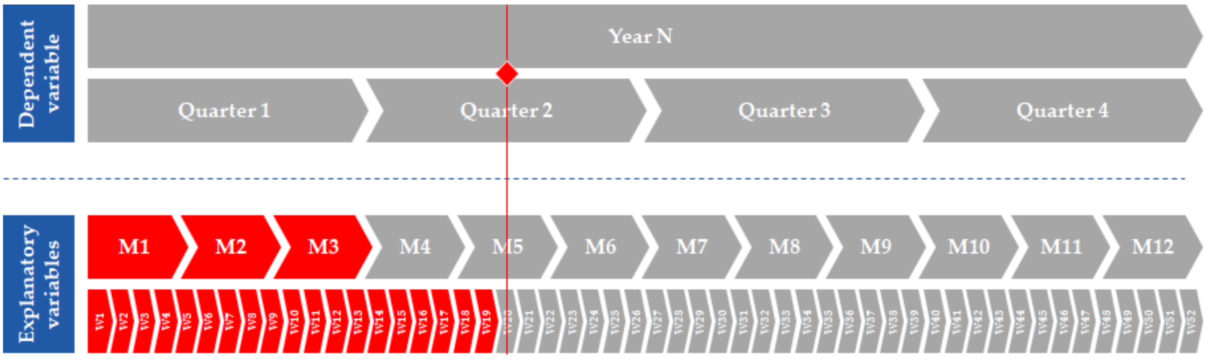
Section 1: Data

1.1. Use of high-frequency data

The purpose of this paper is the nowcasting of global GDP quarterly (or annual) growth rate y_t by exploiting the infra-quarterly (or infra-annual) information available through monthly or weekly indicators as represented in **Figure 1**. The red square figures a given date – around May 10th in this example – and available information appear in red. Official GDP data for Q1 are not yet available (they are published around 2 months after quarter end); monthly indicators are available only until month 3 (they are published at best around 20 days after month end) but weekly data are available up to the preceding week. This illustrates how timeliness is a strong comparative advantage of weekly data and the main reason why one can consider incorporating it in a nowcasting model.

Facing a lack of "world" variables – or their lack of timeliness when such series exist, our approach rely instead on pooling national statistics across multiple countries. We build a large cross-national dataset from which we can aggregate the information into a few factors by principal component analysis (PCA). To that aim, we gather a dataset of 718 monthly and 255 weekly series covering a wide range of economic activities and countries (accounting for around 90% of world GDP in PPP terms) described in **Table A2.1** in **Annex 2**.

Figure 1. Approach to nowcasting annual / quarterly world GDP growth



The 718 monthly series pertain to various aspects of the economy: households' consumption (retail sales, consumer confidence, car registrations), housing, labour market (number of employees, unemployment rates), industrial production and trade. It also covers the nominal side with CPI, PPI, M2 aggregate, and real effective exchange rates. It finally includes the Purchase Managers' Indices (PMI) which have a double advantage of timeliness – they are released the day after month end – and significant predictive power (Harris, 1991; d'Agostino and Schnatz, 2012). Notably, Lahiri and Monokroussos (2011) find evidence that PMIs improve forecast accuracy in factor models. In addition to the "headline" indices, sub-indices for trade ("new export orders") and those capturing tensions in the production apparatus at an early stage ("new orders", "suppliers' delivery time", "output", and "output prices") are included.

As regards weekly data, while the literature generally only considers financial variables at such high frequency (e.g. Andreou *et al.*, 2013), several series in our dataset relate to the "real" economy. We include China housing price indices, commodity prices, trade indices (e.g. Baltic Dry Index), and various indices for the US economy (e.g. new jobless claims, gasoline consumption, steel production, US business condition index of Aruoba *et al.* (2009)). While more weekly data from countries besides US and China would have been desirable, no data with sufficient timespan was available to the best of our knowledge. In addition, gains in forecasting accuracy from US-/China-centric data might still be valuable given their major role in global dynamics. In this vein, Kindberg-Hanlon and Sokol (2018) have documented a high correlation between US data and world GDP growth.[1] Chiu *et al.* (2020) have also demonstrated a high correlation between the Baltic dry index and business cycles in BRICS, suggesting that this series can account for dynamics in emerging economies.

As is more standard in the literature, our weekly dataset also includes financial variables: stock market indexes, nominal effective exchange rates, 3-month interbank rates, and 10-year sovereign rates. The term spread, computed as the difference between the latter two, is included as well as other global or aggregate financial indices (e.g. Standard & Poor's Global

[1] The authors show that only PMIs and industrial production data – included in our monthly dataset – display a higher degree of correlation with world GDP growth than the indicators for the US economy.

1200, VIX). All these variables are retrieved for around 40 countries accounting all together for around 90% of world GDP in PPP terms.

1.2. Handling high-frequency data

An issue arising for monthly data with asynchronous publication lags is that the dataset has a “ragged-edge” pattern: monthly indicators can have different missing elements at the end of the sample – making the monthly dataset unbalanced. To address this, we use the “vertical realignment” procedure of Altissimo *et al.* (2006). For every series, the last available point is taken as the contemporaneous value and the entire series is realigned accordingly. Formally, for a series x_t whose last observation at a contemporaneous date T is at $T-k$, the series becomes $\bar{x}_t = x_{t-k}$.[2] While several issues may be induced by this method – most notably that the availability of data determines dynamic cross-correlation between variables and can then change over time, Marcellino and Schumacher (2010) empirically test other methods and find no substantial changes on the nowcasting performance across these methods.[3]

While the “ragged-edge” pattern does not affect our timely weekly dataset, ensuring stationarity and seasonality are concerns given the absence of well-established method for the seasonal adjustment of weekly series. Both issues might be alleviated by taking the annual growth rate of the series as in Lewis *et al.* (2020). But while statistically correct, this approach introduces a base effect which might be problematic for our objective: as most indicators suffered a dramatic drop in March 2020, the jump in March 2021 will be symmetrically dramatic and might put at risk the viability of the nowcasting. More broadly, Ladiray *et al.* (2018) discuss the drawbacks of taking annual growth for weekly data and point out that it not only includes a phase shift by design but also can introduce spurious cycles.

To alleviate these concerns, we use a two-step procedure to obtain de-seasonalised and stationary weekly indicators. In the first step, non-stationary series are transformed in their average weekly variation over the last four weeks.[4] This transformation – equivalent to a moving monthly growth – have the double advantage of making the series stationary and correcting for infra-monthly seasonality. Then the transformed series is regressed on monthly dummies; the final series is the residual of this regression. This last step allows us to correct for any monthly (or lower frequency) seasonality. To avoid potential distortions that could be caused by the unusual behaviour of some variables during the Covid-19 crisis (e.g. the peak

[2] We impose a maximum lag of 12 months so that the number of observations deleted at the beginning of the sample – due to the vertical realignment – is at most 12 (i.e. 4 in quarterly terms).

[3] Specifically, the authors also test for the EM-algorithm of Stock and Watson (2002) and the Kalman smoother estimates of Doz *et al.* (2006).

[4] This transformation is not applied to series that are already stationary, notably interest rates (3-month interbank and 10-year sovereign), spreads and some US indicators (e.g. VIX, US National Financial Conditions Index of the Chicago Fed, US business condition index of Aruoba *et al.*, 2009).

at 6.6 million initial jobless claims in the US in the last week of March 2020 *vs.* a maximum of 660,000 over 2001-2019), the regression with monthly dummies is estimated over 2001-2019.

Section 2: Extending the FA-MIDAS model with variable pre-selection

2.1. The FA-MIDAS model

Our econometric framework is based on the two-step FA-MIDAS approach proposed by Marcellino and Schumacher (2010). The first step is a principal component analysis, run on both the monthly and weekly datasets. Doing so, we extract the common trends at both frequencies. Formally, we assume that the dataset X_T can be represented according to a factor structure with a r-dimensional factor vector F_T, Λ the loadings matrix and an idiosyncratic components ξ_T not explained by the common factors. The common components ($\Lambda \cdot F_T$) and the idiosyncratic components are mutually orthogonal.

$$X_T = \Lambda \cdot F_T + \xi_T$$

Once monthly and weekly factors have been extracted, the second step is the modelling in a MIDAS specification in which the dependent variable y_t is the quarter-on-quarter growth rate of world GDP at quarter t. MIDAS regression builds on the seminal work by Ghysels *et al.* (2004) showing that this specification – by allocating different weights to the different lags of high-frequency regressors – performs better than a flat aggregation where high-frequency regressors are averaged at lower-frequency. Explanatory variables are a quarterly constant β_0 as well as the monthly $f_{t/3}^{m}$ and weekly $f_{t/13}^{w}$ factors. K represents the number of high-frequency lags and θ is a vector of parameters of the MIDAS weighting function g.

$$y_t = \beta_0 + g\left(f_{t/3}^{m}, \theta^m, K^m, \ldots\right) + g\left(f_{t/13}^{w}, \theta^w, K^w, \ldots\right) + \varepsilon_t$$

The MIDAS weighting function (g) used is a "Almon" polynomial of degree p = 3. The coefficients for the lags of the high-frequency regressor are modelled through a polynomial function of degree $p - 1$. This specification is the most parsimonious since only p parameters are estimated. Formally, the weighting function is:

$$g(f_t, \theta, K, p) = \sum_{k=0}^{K} c(k, \theta) \cdot f_{t-k} \ where\ c(k, \theta) = \sum_{j=0}^{p-1} k^j \cdot \theta_j$$

The optimal number of lags is determined by minimizing the in-sample sum of squared residuals while fixing an upper limit of 4 lags for monthly factor and 8 for weekly factor. The number of high-frequency lags can be different between the monthly and the weekly factors.

2.2. *Pre-selection of regressors*

When forecasting with a high-dimensional dataset, the literature (Bai and Ng, 2008; Schumacher, 2010) concludes that the accuracy of factor models is significantly improved when selecting fewer but more informative predictors. On a more theoretical ground, Boivin and Ng (2006) find that larger datasets lead to poorer forecasting performances when idiosyncratic errors are cross-correlated or when the variables with higher predictive power are dominated.

Against this background, we extend the FA-MIDAS approach by adding a preliminary step to select the regressors with the highest predictive power. The initial dataset is $X_t = (x_{1,t}, x_{2,t}, \dots, x_{N,t})'$ with $t = 1, \dots, T$ and N variables (N^m = 718 for the monthly dataset and N^w = 255 for the weekly dataset). Both figures largely exceed the number of observations T = 81 (2001Q1-2021Q1). The idea underlying pre-selection is to rank the potential regressors $x_{i,t}$ based on a measure of their predictive power with respect to the target variable. In the following, three main techniques are used:

- t-stat ranking (t-stat): each potential regressor $x_{i,t}$ is ranked based on the absolute value of the t-statistic associated with its coefficient estimates in a univariate regression of $x_{i,t}$ on the target variable y_t. The univariate regression also includes four lags of the dependent variable to control for the dynamics of the dependent variable. While originating in genetic studies (Bair *et al.*, 2006), this pre-selection technique has found its way to economics – see for example Jurado *et al.* (2015).

- "Sure Independence Screening" (SIS) of Fan and Lv (2008): regressors are ranked based on their marginal correlation with the target predictor. In their theorem 1, Fan and Lv (2008) provide theoretical ground for this approach by demonstrating that it has the sure screening property that *"all important variables survive after applying a variable screening procedure with probability tending to 1"*. This approach has been used for nowcasting in Ferrara and Simoni (2019) or Proietti and Giovannelli (2021).

- Least-Angle Regression (LARS) algorithm (Bai and Ng, 2008): while the two methods above are based on univariate relationships of the regressors with the target variable, this one provides a ranking of the predictors when the presence of the other predictors is taken into account. Essentially, the LARS – developed by Efron *et al.* (2004) – is a computationally efficient iterative forward selection algorithm, less aggressive than peer techniques in eliminating too many predictors correlated with the ones included. Another key advantage of LARS is its generality as Efron *et al.* (2004) showed that the LASSO (Tibshirani, 1996) is in fact a special case of the LARS. By extension, the LARS algorithm can also be used to solve the optimization criterion of the Elastic Net (Zou and Hastie, 2005). The algorithm is formally defined in **Annex 3** but briefly, starting from no predictors, it adds one at each step by proceeding equiangularly between the variables in the most correlated set. The algorithm adds one regressor at each step, meaning that if we end after k steps, it provides an active set of k predictors. By continuing until the max number of predictors, the algorithm then provides an ordering of potential regressors $x_{i,t}$ according to the iteration at which they join the active set. This approach had been used in several nowcasting studies such as Schumacher (2010), Bulligan *et al.* (2015) or Sousa and Falagiardia (2015).

Once a ranking of the potential regressors $x_{i,t}$ is obtained, pre-selection is about defining the optimal number k^* of regressors to include into the regression. In practice, k^* is chosen by testing over different values and electing the one optimizing the criterion set by the forecaster. In our FA-MIDAS approach, this means estimating different factor models using different subsets $X_t^k = (x_{1,t}^*, x_{2,t}^*, \dots, x_{k,t}^*)$ consisting of the k predictors with the highest scores. In our case with distinct monthly and weekly factors, the optimal numbers of monthly and weekly regressors (respectively $k^{m,*}$ and $k^{w,*}$) are obtained simultaneously by testing over different combinations of (k^m, k^w).

Section 3: Comparing performances across models

3.1. Set of FA-MIDAS models

To test whether high-frequency data improves predictive accuracy of the nowcasting, we compare performances for three different FA-MIDAS models described below. In addition, we also test an AR model with the latest available data for quarterly world GDP.

- **Model 1** includes the monthly factor (f_t^m) and the weekly factor (f_t^w).
- **Model 2** includes a factor at monthly frequency, but which incorporates also weekly series averaged over the month ($f_t^{m,w}$).[5] Comparing model 1 *vs.* model 2 allows us to test whether a three-frequency model performs better than a two-frequency model where weekly indicators are averaged at a monthly frequency.
- **Model 3** includes the monthly factor (f_t^m). Comparing model 1 (model 2) *vs.* model 3 allows us to test whether weekly data can improve nowcasting performances.

Model comparisons are based on the root mean squared errors (RMSE). Out-of-sample errors are computed over 2005Q2-2021Q1 to capture both the Great Financial Crisis and the Great Lockdown. Nowcasts are one-period ahead forecasts: the initial estimation sample is 2001Q1

[5] In this case, it should be noted that the ranking of potential regressors is made over the joint sample of monthly series and weekly series averaged over the month: in other words, this is a common ranking of both weekly and monthly variables.

to 2005Q1 and the first forecast is 2005Q2; and so on with the estimation sample extended by one quarter following an "expanding window" procedure.

3.2. Real-time exercise

To reflect the fact that the nowcasting would be done in real-time, we run estimations for the first, second, and third months of the quarter. The information taken into consideration differs for each month m_i to reflect what would have been available to the forecaster in real-time. We generally consider that the nowcast takes place around the 25th day of month $m_i + 1$:[6] last quarter growth is then available only from the 3rd month onwards – in line with an average publication lag of 2 months for GDP statistics; monthly variables are available up to the month m_i,[7] and weekly variables up to the 3rd week of month $m_i + 1$ given their timeliness. Data availability is recapitulated in **Table 1**.[8]

Table 1. Data availability for each "month" of the nowcasting

	1st month	*2nd month*	*3rd month*
Quarterly variable	2 quarters lag	2 quarters lag	1 quarter lag
Monthly variables	Up to 1st month	Up to 2nd month	Up to 3rd month
Weekly variables	Up to 3rd week of 2nd month	Up to 3rd week of 3rd month	Up to final week of 3rd month

To further mimic a real-time set-up, the ranking of regressors and the calibration of the optimal number of regressors are re-estimated at each date, following the procedure shown

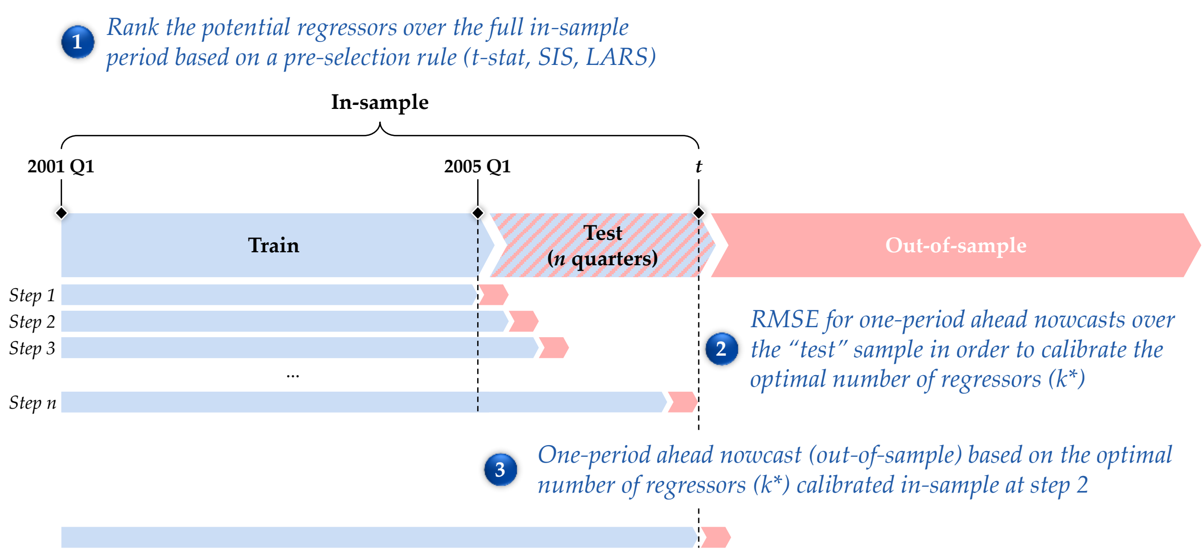
[6] For example, it means that the nowcasting for "1st month" is performed around day 25 of the 2nd month. The numbering relates to the availability of the monthly factor – rather than to the moment of the nowcast: "1st month" means that the monthly factor for 1st month is available, not that the nowcast takes place in the 1st month.

[7] The "vertical realignment" procedure of Altissimo *et al.* (2006) is particularly convenient at this stage since it transposes past publication lags. Indeed, if publication lags are constant over time, the value at any month m_0 in the past of the factor estimated contemporaneously at $m = m_0 + \tau$ is the exact same value as what would have been estimated with information available at m_0 – not accounting for the revisions between m_0 and m.

[8] However, due to the data unavailability of the vintages for many series, the analysis can only be conducted in pseudo real-time: it is not based on vintages that would have reflected the exact information set available to forecasters at the time of forecasting but rather mimics the availability of series due to publication delays. Another difference between our approach and a "pure" real-time approach is that the seasonal adjustment is performed once over the entire sample – and not once at each point with the data that would have been available at the moment of the nowcasting. This first reflects the fact that most series in the dataset are retrieved already seasonally adjusted from the data sources (and for some, e.g. PMIs, without having the possibility to retrieve the unadjusted series). In addition, empirical checks show that the difference between the two approaches (once for the entire sample or progressively with data available up to this point) yields very similar profiles for the resulting series. Only the Covid-19 period is found to induce distortions for some weekly data whose behaviour has been hugely unusual in 2020 (e.g. US initial jobless claims which reached a peak at 6.6 million in the last week of March 2020, 1,000 more than the maximum level over 1990-2019). The Covid-19 has therefore been excluded from the sample on which parameters for seasonal adjustment are calibrated.

in **Figure 2**. At date t, the ranking of regressors is performed over the in-sample period only (step 1 in **Figure 2**) mimicking the exact information that would have been available to the real-time forecaster at date t. This means that the correlation of potential regressors with the target variable over the out-of-sample period is not considered: while closer to a real-time set-up, this approach however contrasts with most of the literature in which the ranking appears to be performed only once and over the full sample (e.g. Bulligan *et al.*, 2015; Falagiarda and Sousa, 2015), thereby giving further advantage to pre-selection. In addition, to be fully consistent with a real-time exercise, the optimal number of regressors (k^*) is also re-calibrated at each date, also only on the in-sample period. To do so, the in-sample period is split between "train" (2001Q1-2005Q1) and "test" (2005Q2 to t) samples. Then pseudo-out-of-sample nowcasts[9] are made over the "test" sample: at each quarter q, the model is estimated from 2001Q1 to $q-1$ and produce a one-period ahead forecasts for q. This gives a forecast error at q; repeating this procedure over the whole "test" sample gives a pseudo-out-of-sample RMSE. This procedure (step 2 in **Figure 2**) is repeated across all possible values k of potential regressors. In the end, the optimal number of regressors k^* chosen as the one minimizing the RMSE over the "test" sample.[10] The FA-MIDAS model with k^* regressors is then used to produce an out-of-sample one-period-ahead of world GDP growth at $t+1$ (step 3 in **Figure 2**). This way, the optimal number of regressors varies at each date t, as well as the ranking of regressors.

Figure 2. Real-time set-up for the pre-selection



[9] "Pseudo out-of-sample" since the ranking of regressors is made over the entire in-sample period, thereby also including the "test" period.

[10] For model 1 with both weekly and monthly factors, this procedure is applied across all possible couples (k^m, k^w) indicating the number of respectively monthly and weekly series included in the factors.

Section 4: Results

4.1. Pre-selection techniques

Results for the different pre-selection techniques are presented in **Table 2**.[11] Pre-selection in a FA-MIDAS yields accuracy gains up to 13% in terms of out-of-sample performances, on average over the three months, against the alternative of no pre-selection. However, gains are only timid for the first month: in the case of the LARS, 6% accuracy gains at month 1 compared with around 18% at months 2 and 3. It is notable that such gains arise even with a strict real-time set-up. When the pre-selection is not run in real-time (i.e. when the ranking of regressors is instead performed only once and over the entire sample, as in some of the literature), accuracy gains can reach up to 66% as shown in **Table A1.1** in **Annex 1**.

A second finding in **Table 2** is that the LARS procedure (Bai and Ng, 2008) exhibits better performances than other techniques. In the rest of the paper, FA-MIDAS models are based on this pre-selection technique with, as described in **section 3.2**, the optimal number of regressors $k^{*}_{m_i,t,j}$ specific to each month m_i of the quarter ($i = \{1,2,3\}$), each date t (between 2005Q2 and 2021Q1), and each model j ($j = \{1,2,3\}$). In addition, for model 1 with both weekly and monthly factors, the optimal numbers of respectively monthly and weekly series is a couple $(k^{m,*}_{m_i,t,j}, k^{w,*}_{m_i,t,j})$ with $k^{m,*}_{m_i,t,j}$ possibly different from $k^{w,*}_{m_i,t,j}$.

Table 2. Out-of-sample RMSE across pre-selection techniques and months of the quarter

		1st month	2nd month	3rd month	*Average*
FA-MIDAS	No pre-selection	0.973	1.350	1.635	*1.319*
	LARS	0.913	1.107	1.365	*1.147*
	SIS	1.108	1.279	1.440	*1.275*
	t-stat	1.264	1.269	1.386	*1.307*
LASSO-MIDAS		1.585	1.532	1.556	*1.558*

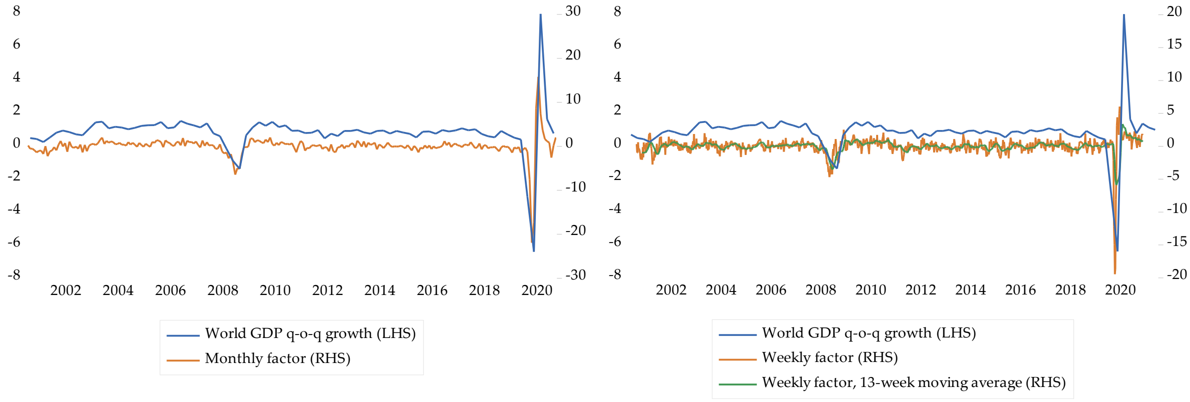
Grey cells indicate best performance for a given month (or the average of the three months)

The factors obtained for the monthly and weekly datasets at t = 2021Q1 and for the month m_3 are displayed in **Figure 3**.[12] Both appear to track adequately world GDP and to be leading indicators of turning points in the global economy with a 1-3 months lead.

[11] Results are reported for the model 1. While not reported, the results for other models are similar.
[12] Based on the Bai and Ng (2002) information criterion and on its modified version in Alessi *et al.* (2010), the optimal number of factors to include in the regression is determined to be one.

Figure 3. Factors and world GDP growth

Monthly factor | *Weekly factor*



Note: factors are computed using the optimal number of regressors for a LARS technique, for month 3, and at 2021Q1 (meaning with ranking of regressors over 2001Q1-2020Q4 and calibration of optimal number of variables for one-period out-of-sample forecasts over 2005Q2-2020Q4, cf. ***section 3.2****). the optimal number of regressors can be different for monthly (LHS) and weekly (RHS) frequencies.*

In the lower part of **Table 2**, we also compare performances of the FA-MIDAS with the LASSO-MIDAS, another dimension reduction technique suited for a mixed-frequency setting. LASSO is a sparse approach based on a penalized regression. Contrary to the FA-MIDAS, it performs both the selection of regressors and the estimation of the mixed-frequency equation in a single step. The LASSO-MIDAS is a recent addition to the literature (Marsilli, 2014; Uematsu and Tanaka, 2019; Mogliani and Simoni, 2021) and the model used in this paper is the sparse-group LASSO of Babii *et al.* (2021). The interest of the "group-LASSO" over the unstructured LASSO is that for a given regressor, either all high-frequency lags enter the regression, or all are set to zero. Said otherwise, it does not select only some of the lags of a high-frequency regressor while setting other lags of the same regressor at zero, as would do an unstructured LASSO-MIDAS. This approach is therefore more consistent with our FA-MIDAS, and also more interpretable for a practitioner. Two other advantages of the group-LASSO are its computational efficiency and – as shown by Babii *et al.* (2021) – the fact that it outperforms the unstructured LASSO.

The comparison shows that the FA-MIDAS outperforms the LASSO-MIDAS. This might seem in line with Giannone *et al.* (2021) showing that "sparse" methods – such as the LASSO – perform better than "dense" approaches – such as factor models – only if the data generating process is of very low dimension. In the case of this paper, where the prediction of a global variable relies on various national indicators, such sparsity might be unlikely.[13]

4.1. Model comparison

Model performances are reported in **Table 3**. Both in- and out-of-sample RMSE suggest that weekly data improve nowcasting accuracy. Models with weekly data (1 and 2) generally

[13] Also, very few variables are kept with the LASSO-MIDAS (2 monthly and 2 weekly for the last iteration with estimation up to 2020Q4), which might explain the limited performances of such a model.

outperform the model with only monthly data (3), and largely outperform the AR model. Among models with weekly data, it appears that model 1 which includes a separated weekly factor yields better performances – with the exception of month 1 in the out-of-sample exercise – than the model incorporating weekly series with monthly data in a unique factor (model 2).

Table 3. Performances (RMSE) relative to the AR model

	FA-MIDAS			AR model
	Model 1	Model 2	Model 3	
In-sample				
1st month	0.291	0.341	0.350	1.000
2nd month	0.215	0.299	0.352	1.000
3rd month	0.195	0.334	0.260	1.000
Out-of-sample				
1st month	0.521	0.467	0.483	1.000
2nd month	0.631	0.677	0.771	1.000
3rd month	0.601	0.631	0.633	1.000

Grey cells indicate best performance for a given month. Model 1 includes both a weekly and a monthly factor, model 2 includes a unique factor with both monthly and weekly data (averaged over the month), model 3 is based only on monthly data.

We assess the significance of differences in predictive accuracy using the Diebold and Mariano (1995) test with the Harvey *et al.* (1997) corrected variance for small-sample bias. Results are reported in **Table 4**. Model 1 is found to have significantly better predictive accuracy than model 3 and the AR model at month 2, while also outperforming the AR model at month 1. No significant differences however arise at month 3. It confirms that relying on weekly data can drive significant improvements in accuracy against models that rely solely on monthly or quarterly data, though these gains are broad-based across all months of the quarter. Since nested models can weaken the inference in Diebold-Mariano tests (Clark and McCracken, 2001), we complement this analysis with a Model Confidence Set (MCS) test of Hansen *et al.* (2011)[14] in **Table A1.2** in **Annex 1**: for months 2 and 3 of the quarter, the model 1 is always elected as the best model and the only remaining in the $\mathcal{M}^*_{50}$.

[14] The MCS test estimates a set of superior models from an initial set of models where the "superiority" is defined by a user-specified loss function. It consists in a stepwise procedure in which the null hypothesis H_0 of "all selected models perform identically" is repeatedly tested with respect to the expected loss function. Upon rejection, model is removed from the set and the procedure is the repeated. In addition to the issue of possibly nested models, one other advantage of MCS over pairwise tests – such as the Diebold-Mariano test – is that it allows for an asymptotic control of the family-wise error rate which might be problematic when conducting sequences of pairwise tests.

Table 4. Diebold-Mariano (1995) test results

	Model 1 *vs.* model 2	Model 1 *vs.* model 3	Model 1 *vs.* AR model
1st month	0.91	0.77	**0.06**
2nd month	0.22	**0.06**	**0.08**
3rd month	0.14	0.14	0.21

Bold values indicate where the null hypothesis can be rejected at a 10% significance. Results report p-value for H_0 = model A have lower accuracy than model B over 2005Q1-2021Q1. Model 1 includes both a weekly and a monthly factor, model 2 includes a monthly factor incorporating monthly and weekly data (averaged over the month), model 3 is based only on monthly data.

4.2. *"Crisis" vs. "normal" periods*

A recent strand of literature has documented state-dependent performances of forecasting models (Chauvet *et al.*, 2013; Siliverstovs and Wochner 2020; Siliverstovs 2020; 2021) which can differ depending on the state of the business cycle such as recessionary *vs.* expansionary period. The possibility of asymmetries in forecasting performances is even greater with high-frequency data given the general trade-off between timeliness and accuracy (Ahnert and Bier, 2001): such data provide a timely signal which can enhance nowcasting performance if economic conditions suddenly deteriorate but during "normal" periods, their contribution might be only of second order.

Against this background, we distinguish our sample between "normal" and "crisis" episodes, and then compute the in- and out-of-sample RMSE for both sub-samples.[15] Results are reported in **Table 5** where it appears that models 1 and 2 with weekly data heavily outperform others during "crisis" episodes. During those periods, the upside of providing a very timely signal likely exceeds the downside of noise in the weekly data. However, during "normal" periods, those models have performances closer to those of models relying on monthly data (model 3) or on AR terms. In particular, the relative performances of FA-MIDAS models over the AR benchmark tend to be higher during "crisis" periods. For instance, model 1 entails on average a 42% improvement in predictive accuracy compared with the AR during "crisis" episodes, but 33% during "normal" episodes.

Table 5. Performances (RMSE) relative to the AR model – by sub-periods

	FA-MIDAS			AR model
	Model 1	Model 2	Model 3	
Crisis episodes				
In-sample				

[15] Regressions are still estimated over full sample – or for out-of-sample over the sample preceding target quarter.

1st month	0.257	0.317	0.324	1.000
2nd month	0.146	0.279	0.325	1.000
3rd month	0.089	0.255	0.199	1.000
Out-of-sample				
1st month	0.518	0.461	0.477	1.000
2nd month	0.633	0.680	0.777	1.000
3rd month	0.599	0.630	0.631	1.000
Non-crisis episodes				
In-sample				
1st month	0.595	0.535	0.586	1.000
2nd month	0.649	0.512	0.576	1.000
3rd month	0.760	0.978	0.763	1.000
Out-of-sample				
1st month	0.595	0.635	0.648	1.000
2nd month	0.563	0.566	0.541	1.000
3rd month	0.845	0.805	0.867	1.000

Grey cells indicate best performance for a given month. Model 1 includes both a weekly and a monthly factor, model 2 includes a unique factor with both monthly and weekly data (averaged over the month), model 3 is based only on monthly data.

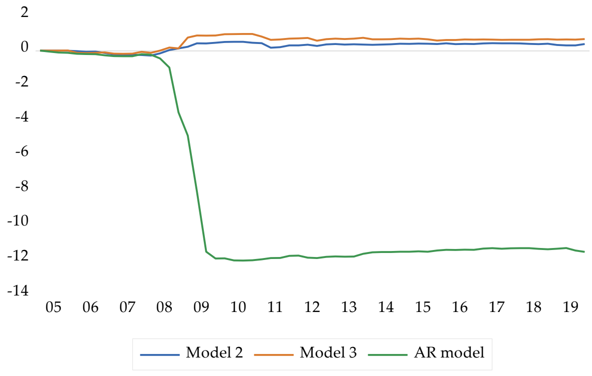
Following Welsh and Goyal (2008) or more recently Siliverstovs (2020; 2021), we complement this assessment with Cumulative Sum of Squared Forecast Errors (CSSFED). Unlike the analysis based on RMSE – which averages over several quarters, the CSSFED allows to follow the evolution of the relative forecasting performances of two models i and j. A decreasing CSSFED indicates that model i outperforms model j. When CSSFED is broadly stable, predictive performances of model i and j can be considered as similar. Formally if $\hat{e}_{i,t}$ is model i's forecast error, the CSSFED is defined as follows:

$$CSSFED_{[0,T]} = \sum_{t=0}^{T} [\hat{e}_{i,t}^2 - \hat{e}_{j,t}^2],$$

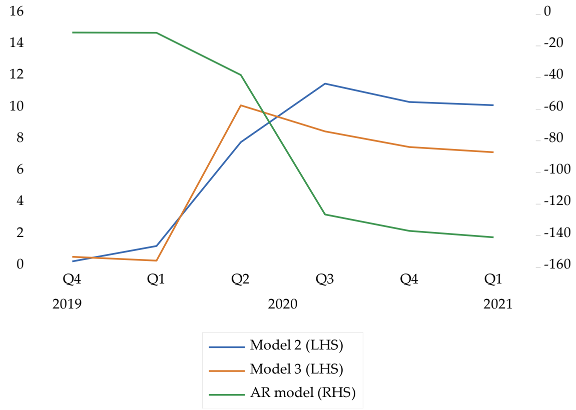
Figure 4. CSSFED (out-of-sample) of model 1 compared to other models

Panel A. Month 1

2005Q1-2019Q4

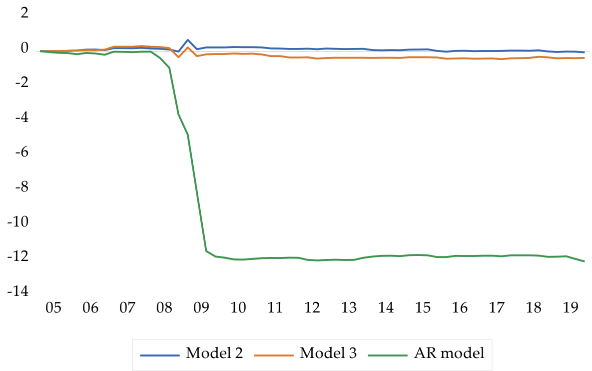


2019Q4 – 2021Q1

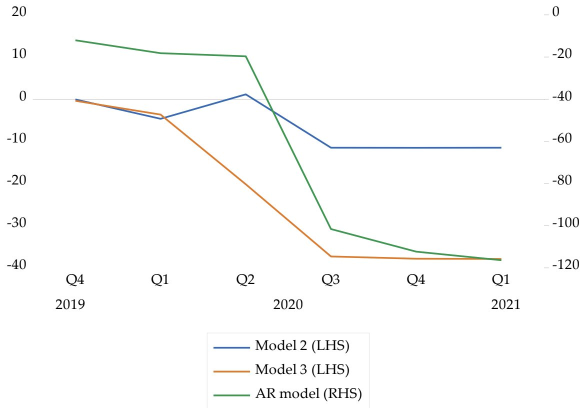


Panel B. Month 2

2005Q1-2019Q4

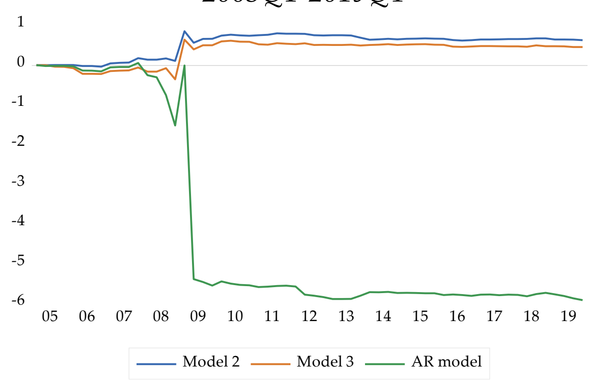


2019Q4 – 2021Q1



Panel C. Month 3

2005Q1-2019Q4



2019Q4 – 2021Q1

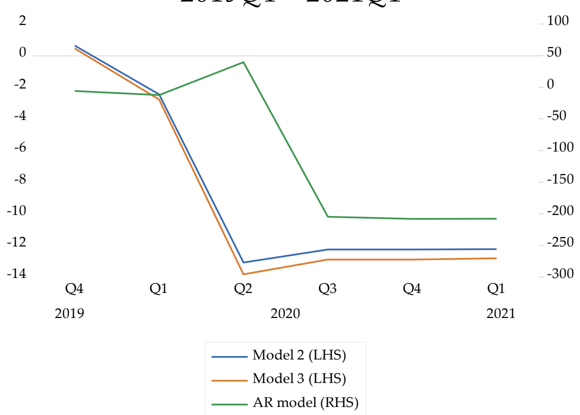


Figure 4 reports CSSFED based on one-period ahead out-of-sample forecast errors, comparing model 1 (as model *i* in the definition above) with others. For the sake of visibility, we separated into pre- and post-Covid-19 samples. Compared with the AR benchmark (green line), the differences are highly visible at the moments of large crisis (2008-2009 and 2020-2021) and for all months of the quarter. Over other periods however, the line is broadly flat, indicating that performances of model 1 and the AR benchmark are broadly similar. This finding points to state-dependent relative performances of model 1 relatively to a simple AR benchmark, consistent with the aforementioned literature on asymmetries of forecasting performances

across the business cycle. When comparing model 1 with models 2 and 3, large differences arise only around the Covid-19 crisis. There are some differences around the GFC but whose magnitude is very limited. The differences jump in 2020Q2 and 2020Q3 with model 1 largely outperforming others at months 2 and 3 (and conversely for month 1).

This suggests that high-frequency data would have markedly enhance accuracy during the Covid-19 crisis – but not during the GFC. It should be noted however that the above result is partly driven by our strict real-time set-up (see **section 3.2**). When this assumption is relaxed and the ranking of regressors is instead performed over the full sample, results for the CSSFED are shown in **Figure A1.1** in **Annex 1**. It appears that under this alternative set-up, model 1 appear to outperform other models during the Great Financial Crisis and that gains can be reached with model 1 also at month 1 of the quarter. This calls for caution when using pre-selection since using a "pseudo real-time" set-up can lead to different results than a "real-time" framework.

4.3. Annual GDP forecasts

Back to the issue highlighted in the introduction, the main concern for "projection-takers" macroeconomists during the Covid-19 crisis has been the rapid obsolescence of "benchmark" world GDP forecasts. Building on our results that weekly data significantly improve forecast performance during these crisis episodes, we construct a nowcasting model for the annual growth rate of world GDP based on a FA-MIDAS specification. This model predicts the annual growth rate of world GDP y_t^{annual} using the carry-over c_t^q provided by the known quarterly growth rates – and whose coefficient is fixed to 1 in the regression, the monthly factor (f_t^m) and the weekly factor (f_t^w).[16] Formally:

$$y_t^{annual} = \beta_0 + c_t^q + g\left(f_{t/_{12}}^m, \theta^m, K^m, \ldots\right) + g\left(f_{t/_{52}}^w, \theta^w, K^w, \ldots\right) + \varepsilon_t$$

We start by comparing performances across different models to test if weekly data still enhance predictive accuracy for annual forecasts. In-sample RMSE are reported in **Figure A1.2** in **Annex 1** where we compare the model described above with three alternatives: a model without the weekly factor; a model with only the carry-over; and an AR model. Our baseline model appears to outperform others for all weeks of the year.

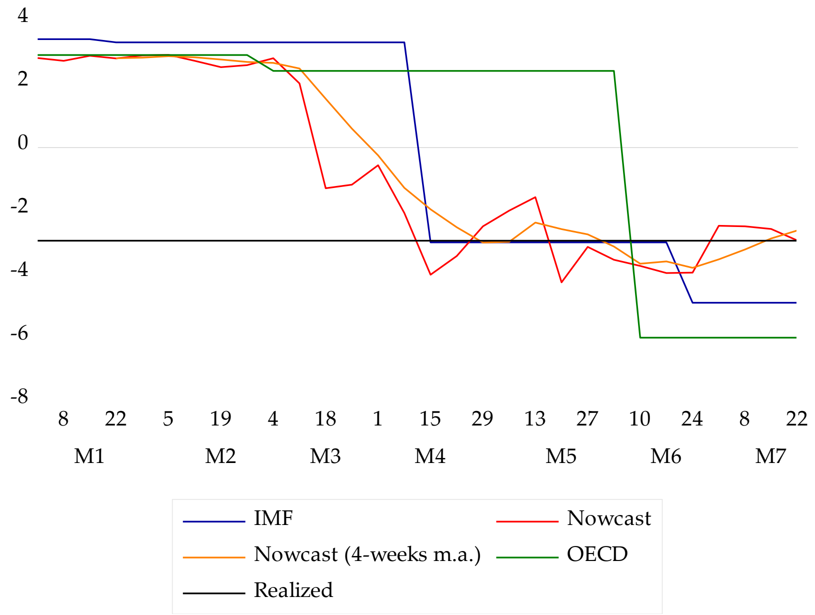
We finally compare in **Figure 5** the pseudo real-time forecasts of our model with the projections released by the OECD and the IMF. We run a "pseudo real-time" comparison in which FA-MIDAS is re-estimated at the end of each week with the information available at this stage.[17] It shows that the nowcasting has the advantage of greater timeliness and decent

[16] For the annual exercise, contrary to the quarterly exercise, the optimal number of variables is not selected for each week of the year. The monthly (weekly) factor is the principal component from the 60 (20) first series that LARS select.

[17] We however do not apply the full procedure described in **section 3.2** at the annual frequency, since the very limited number of annual data points (22) would prevent any distinction of a train and test sample for the in-

accuracy compared with IMF's or OECD's forecasts as the former seems to have a 1 to 3 months lead on the latter. This suggests that a nowcasting based on high-frequency data can provide an alternative "benchmark" projection during crisis episodes. Fortunately, this is the moment when it is most needed (due the obsolescence of usual "benchmark" projections) and this coincides with the moment when high-frequency data most greatly enhance predictive performances.

Figure 5. Pseudo real-time nowcast and forecasts for the annual world GDP growth in 2020



Conclusion

Our paper provides evidence that including high-frequency (weekly) variables can significantly improve the in- and out-of-sample performances in a FA-MIDAS specification, but only during specific "crisis" episodes. Further analysis reveals that performances of models with weekly data are broadly similar to those of an AR model during "normal" periods when activity remains broadly stable. Large differences in predictive accuracy between models with weekly data and AR models happen only during "crisis" episodes (2008-2009 and 2020-2021, i.e. 12 quarterly observations on a total estimation sample of 81 observations). This finding points to strong asymmetries in nowcasting performances following the literature on state-dependent relative performances of sophisticated models *vs.* the AR benchmark (e.g. Siliverstovs, 2020; 2021). In addition, when comparing models with weekly data to models relying on monthly data, performances are alike during "normal" periods but also during the Great Financial Crisis (2008-2009). The only differences arise at the moment of the Covid-19 crisis. In other terms, weekly data greatly contributes to nowcasting period only during the Covid-19 episode when its timeliness could make up for the long

sample period. Instead we rely on a ranking of regressors performed once – over the full sample – and a fixed number of regressors (see footnote above). Therefore, this is rather a "pseudo out-of-sample" exercise in contrast with the set-up for quarterly nowcasts.

publication lags in standard monthly indicators but does not yield significant benefits during other periods, even the Great Financial Crisis. Finally, the paper shows that higher accuracy can be reached when weekly data is introduced in a specific weekly factor rather than when it is averaged over the month and incorporated along monthly variables.

The paper also provides evidence that a pre-selection of variables enhances markedly the forecasting performances of a FA-MIDAS. Among the different techniques tested in this paper, the LARS (Bai and Ng, 2008) gives more substantial gains than alternatives approaches based on univariate relations (SIS and t-stat).

It should be kept in mind that the above results are obtained in a purely data-driven exercise with minimal intervention from the forecaster: large datasets are assembled by the forecaster (around 1,000 variables in total) but the pre-selection of variables and the calibration of the models – notably of the choice of the optimal number of regressors to include – are performed automatically. In addition to being purely data-driven, the set-up is strictly out-of-sample with pre-selection of variables and calibration of the model done only in-sample. Higher and more significant accuracy gains can be reached when relaxing these constraints, for example by running the pre-selection over the full sample: this calls for caution as results of pre-selection under a "pseudo real-time" set-up can largely differ those in a "real-time" set-up.

We also build a real-time nowcasting model for the annual growth of world GDP which has the double advantage of: *(i)* timeliness as it provides a forecast every week while institutional forecasts are updated maximum four times a year; *(ii)* accuracy as it produces forecasts close to IMF's or OECD's projections but with a 1 to 3 month lead. This can provide an alternative "benchmark" for world GDP growth projection to economists. Interestingly during "crisis" episodes, not only such an alternative "benchmark" is needed – since the usual "benchmarks" provided by institutions are rapidly outdated given large and sudden swings in activity – but it is also when high-frequency data would provide the greater gains in predictive accuracy.

An avenue for future research could be the inclusion of further high-frequency data such as card transactions (Cerdeiro *et al.*, 2020), satellite data (Bricongne *et al.*, 2021a), marine traffic (Carvalho *et al.*, 2020), or web-scrapped data (Bricongne *et al.*, 2021b). Their limited timespan – e.g. Google mobility data only starts in January 2020 – or their high cost (e.g. using marine traffic requires several thousand euros) is however a strong limitation. Finally, our approach can be extended to nowcast GDP for a specific country or group of countries (e.g. euro area).

References

d'Agostino A. and Schnatz B. (2012). "Survey-based nowcasting of US growth: a real-time forecast comparison over more than 40 years", *European Central Bank Working Paper Series*, No 1455

Ahnert H. and Bier W. (2001). "Trade-off between timeliness and accuracy", *Economisch Statistische Berichten*, No 4299

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

Altissimo F., Cristadoro R., Forni M., Lippi M., and Veronese G. (2006). "New Eurocoin: Tracking Economic Growth in Real Time", *CEPR Discussion Papers*, No 5633

Andreou E., Ghysels E., and Kourtellos A. (2013). "Should Macroeconomic Forecasters Use Daily Financial Data and How?", *Journal of Business & Economic Statistics*, 31(2), pp. 240-251

Aruoba S., Diebold F., and Scotti C. (2009). "Real-Time Measurement of Business Conditions", *Journal of Business and Economic Statistics*, 27(4), pp. 417-427

Babii A., Ghysels E., and Striaukas J. (2021). "Machine Learning Time Series Regressions with an Application to Nowcasting", *Journal of Business & Economic Statistics*, online publication: https://doi.org/10.1080/07350015.2021.1899933

Bai J. and Ng S. (2002). "Determining the number of factors in approximate factor models", *Econometrica*, 70(1), pp. 191-221

Bai J. and Ng S. (2008). "Forecasting economic time series using targeted predictors", *Journal of Econometrics*, 146(2), pp. 304-317

Bair E., Hastie T., Paul D., and Tibshirani R. (2006). "Prediction by supervised principal components", *Journal of the American Statistical Association*, 101(473), pp. 119-137

Bańbura M., Giannone D., Reichlin L., and Modugno M. (2013). "Now-casting and the real-time data flow", *European Central Bank Working Paper Series*, No 1564

Boivin J. and Ng S. (2006). "Are more data always better for factor analysis", *Journal of Econometrics*, 132, pp. 169–194

Bulligan G., Marcellino M., and Venditti F. (2015). "Forecasting economic activity with targeted predictors", *International Journal of Forecasting*, 31(1), pp. 188-206

Bricongne J-C., Coffinet J., Delbos J-B., Kaiser V., Kien J-N., Kintzler E., Lestrade A., Meunier B., Mouliom M., and Nicolas T. (2020). "Tracking the economy during the Covid-19 pandemic: the contribution of high-frequency indicators", *Bulletin de la Banque de France*, 231

Bricongne J-C., Meunier B., and Pical T. (2021a). "Can satellite data on air pollution predict industrial production?", *Banque de France Working Papers*, No. 847

Bricongne J-C., Meunier B., and Pouget S. (2021b). "Web Scraping Housing Prices in Real-time: the Covid-19 Crisis in the UK", *Banque de France Working Papers,* No. 827

Carvalho V., Garcia J., Hansen S., Ortiz Á., Rodrigo T., Rodríguez Mora J., and Ruiz J. (2020). "Tracking the COVID-19 Crisis with High-Resolution Transaction Data", *Cambridge-INET Working Papers*, No 2016

Cerdeiro D., Komaromi A., Liu Y., and Saeed M. (2020). "World Seaborne Trade in Real Time: A Proof of Concept for Building AIS-based Nowcasts from Scratch", *International Monetary Fund Working Papers*, No 20/57

Chiu C., Chen C., Kuo P.-L., and Wang M. (2020). "The Dynamic Relationships between the Baltic Dry Index and the BRICS Stock Markets: A Wavelet Analysis", *Asian Economic and Financial Review*, 10(3), pp. 340-351

Chernis T., Cheung C., and Velasco G. (2020). "A three-frequency dynamic factor model for nowcasting Canadian provincial GDP growth", *International Journal of Forecasting*, 36(3), pp. 851-872

Chauvet, M. and S. Potter (2013). "Forecasting output". In G. Elliott and A. Timmermann (Eds.), *Handbook of Forecasting*, Volume 2, pp. 1–56. Amsterdam: North Holland.

Chen S., Igan D., Pierri N., and Presbitero A. (2020). "Tracking the Economic Impact of COVID-19 and Mitigation Policies in Europe and the United States", *International Monetary Fund Working Papers*, No 20/125

Clark T. E., and McCracken M. (2001). "Tests of equal forecast accuracy and encompassing for nested models", *Journal of Econometrics*, 105(1), pp. 85-110

Coibion O., Gorodnichenko Y., and Weber M. (2020). "Labor Markets During the COVID-19 Crisis: A Preliminary View", *University of Chicago Working Papers*, No 2020-041

Diebold F. and Mariano R. (1995). "Comparing predictive accuracy", *Journal of Business and Economic Statistics*, 13, pp. 253-263

Doz, C., Giannone D., and Reichlin L. (2006). "A quasi maximum likelihood approach for large approximate dynamic factor models", *European Central Bank Working Paper Series*, No 674

Efron B., Hastie T., Johnstone I. and Tibshirani R. (2004). "Least angle regression", *Annals of Statistics*, 32(2), pp. 407-499

Fan J. and Lv J. (2008). "Sure independence screening for ultrahigh dimensional feature space", *Journal of the Royal Statistical Society Series B*, 70(5), pp. 849-911

Ferrara L. and Marsilli C. (2019). "Nowcasting global economic growth: A factor-augmented mixed-frequency approach", *The World Economy*, 42(3), pp. 846-875

Ferrara L. and Simoni A. (2019). "When are Google data useful to nowcast GDP? An approach via pre-selection and shrinkage", *Center for Research in Economics and Statistics (CREST) Working Papers*, No 2019-04

Ferrara L., Froidevaux A., and Huynh T-L. (2020). "Macroeconomic nowcasting in times of Covid-19 crisis: On the usefulness of alternative data", *Econbrowser*, https://econbrowser.com/archives/2020/03/guest-contribution-macroeconomic-nowcasting-in-times-of-covid-19-crisis-on-the-usefulness-of-alternative-data

Ghysels E., Santa-Clara P., and Valkanov R. (2004). "The MIDAS Touch: Mixed Data Sampling Regression Models", *CIRANO Working Paper*, No 2004-20

Giannone D., Lenza M., and Primiceri G. (2021). "Economic Predictions with Big Data: The Illusion of Sparsity", *European Central Bank Working Paper Series*, No 2542

Golinelli R. and Parigi G. (2014). "Tracking world trade and GDP in real time", *International Journal of Forecasting*, 30(4), pp. 847-862

Hansen P., Lunde A. and J. Nason (2011). "The model confidence set", *Econometrica*, 79(2), pp. 453-497

Harris E. (1991). "Tracking the Economy with the Purchasing Managers' Index", *Federal Reserve Bank of New York Quarterly Review*, Autumn

Harvey D., Leybourne S. and Newbold P. (1997). "Testing the equality of prediction mean squared errors", *International Journal of Forecasting*, 13(2), pp. 281-291

Hastie T., Tibshirani R. and Friedman J. (2008). *The Elements of Statistical Learning*, Springer Series in Statistics, 2nd edition

INSEE (2020). "Les données « haute fréquence » sont surtout utiles à la prévision économique en période de crise brutale", *Note de conjoncture de l'INSEE*, June 17th, https://www.insee.fr/fr/statistiques/4513034?sommaire=4473296

Jurado K., Ludvigson S., and Ng S. (2015). "Measuring Uncertainty", *American Economic Review*, 105(3), pp. 1177-1216

Kindberg-Hanlon G. and Sokol A. (2018). "Gauging the globe: the Bank's approach to nowcasting world GDP", *Bank of England Quarterly Bulletin*, Q3

Ladiray D., Palate J., Mazzi G., and Proietti T. (2018). *"Seasonal Adjustment of Daily and Weekly Data"*, in 16th Conference of the International Association of Official Statisticians, Paris, September 19th-21st, https://www.oecd.org/iaos2018/programme/IAOS-OECD2018_Item_1-A-1-Ladiray_et_al.pdf

Lahiri K. and Monokroussos G. (2011). "Nowcasting US GDP: The role of ISM Business Surveys", *University at Albany Discussion Papers*, No 11-01

Lewis D., Mertens K., and Stock J. (2020). "Monitoring Real Activity in Real Time: The Weekly Economic Index", *Liberty Street Economics*, No 20200330b, Federal Reserve Bank of New York

Matheson T. (2011). "New Indicators for Tracking Growth in Real Time", *International Monetary Fund Working Papers*, No 11/43

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

Marsilli, C. (2014). "Variable Selection in Predictive MIDAS Models", *Banque de France Working papers*, No 520

Mogliani M. and Simoni A. (2021). "Bayesian MIDAS penalized regressions: estimation, selection, and prediction", *Journal of Econometrics*, 222(1), pp 833-860

Proietti T. and Giovannelli A. (2021). "Nowcasting monthly GDP with big data: A model averaging approach", *Journal of the Royal Statistical Society: Series A*, 184(2), pp. 683-706

Schumacher C. (2010). "Factor forecasting using international targeted predictors: The case of German GDP", *Economics Letters*, 107(2), pp. 95–98

Siliverstovs B. (2020). "Assessing nowcast accuracy of US GDP growth in real time: The role of booms and busts", *Empirical Economics*, 58, pp. 7-27

Siliverstovs B. (2021). "New York FED Staff Nowcasts and Reality: What Can We Learn about the Future, the Present, and the Past?", *Econometrics*, 9(1), pp. 1-11

Siliverstovs B. and Wochner D. (2021). "State-dependent evaluation of predictive ability", *Journal of Forecasting*, 40, pp. 547-574

Sousa J. and Falagiarda M. (2015). "Forecasting euro area inflation using targeted predictors: is money coming back?", *European Central Bank Working Paper Series*, No 2015

Stock J. and Watson M. (2002). "Macroeconomic Forecasting Using Diffusion Indexes", *Journal of Business and Economic Statistics*, 20, pp. 147-162

Tibshirani R. (1996). "Regression shrinkage and selection via the lasso", *Journal of Royal Statistical Society Series B*, 58(1), pp. 267-288

Uematsu Y. and Tanaka S. (2019). "High-dimensional macroeconomic forecasting and variable selection via penalized regression", *Econometrics Journal*, 22(1), pp. 34-56

Welch I. and Goyal A. (2008). "A comprehensive look at the empirical performance of equity premium prediction", *Review of Financial Studies*, 21(4), pp. 1455-1508

Zou H. and Hastie T. (2005). "Regularization and variable selection via the elastic net", *Journal of Royal Statistical Society Series B*, 67(2), pp. 301-320

Annex 1: Additional tables

Table A1.1. Out-of-sample RMSE across pre-selection techniques and months of the quarter *(alternative with pre-selection not done in a real-time manner)*

		1st month	2nd month	3rd month	*Average*
FA-MIDAS	No pre-selection	0.973	1.350	1.635	*1.319*
	t-stat	0.834	0.432	0.856	*0.644*
	SIS	0.547	0.473	0.543	*0.508*
	LARS	0.493	0.382	0.971	*0.677*
LASSO-MIDAS		1.585	1.532	1.556	*1.558*

Grey cells indicate best performance for a given month (or for the average of the 3 months)

Table A1.2. Model Confidence Set (Hansen *et al.*, 2011) test results

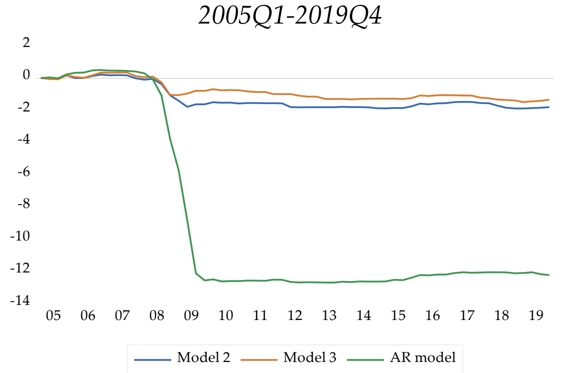
	FA-MIDAS			AR model
	Model 1	Model 2	Model 3	
1st month	0.493	1	0.480	0.109
2nd month	1	0.317	0.329	0.199
3rd month	1	0.398	0.364	0.491

Results report p-values of the statistic T_{max} of Hansen et al. (2011) based on a squared errors loss function. Model 1 includes both a weekly and a monthly factor, model 2 includes a monthly factor incorporating monthly and weekly data (averaged over the month), model 3 is based only on monthly data.

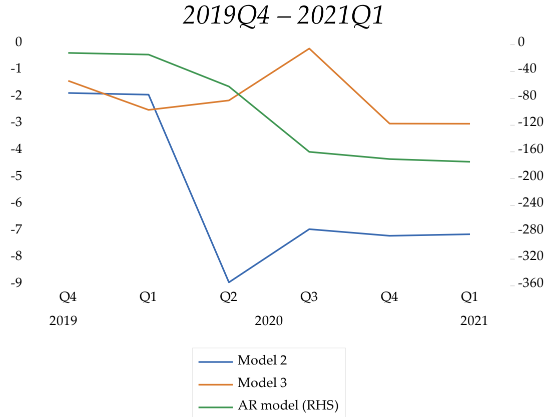
Figure A1.1. CSSFED (pseudo out-of-sample) of model 1 compared to other models

Panel A. Month 1

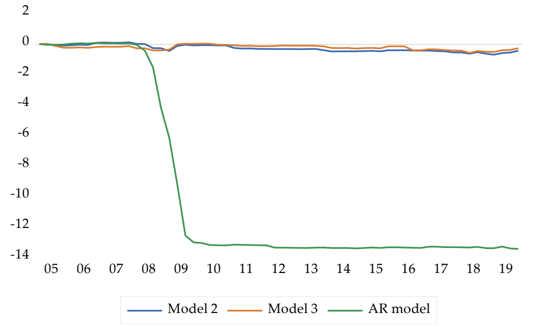
2005Q1-2019Q4

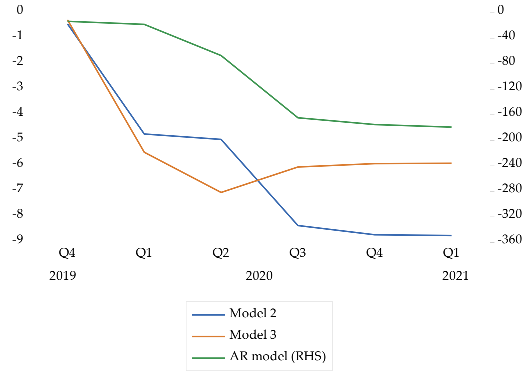


2019Q4 – 2021Q1

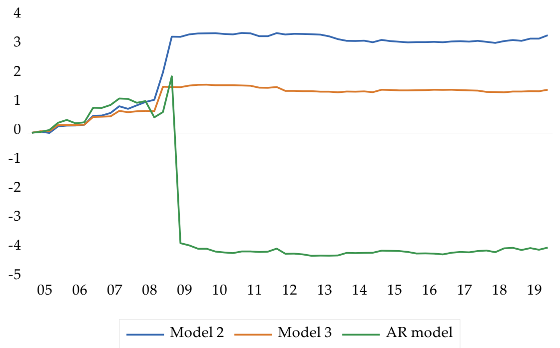


Panel B. Month 2





Panel C. Month 3



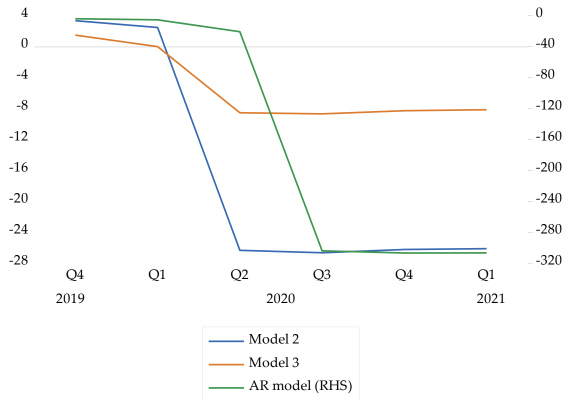
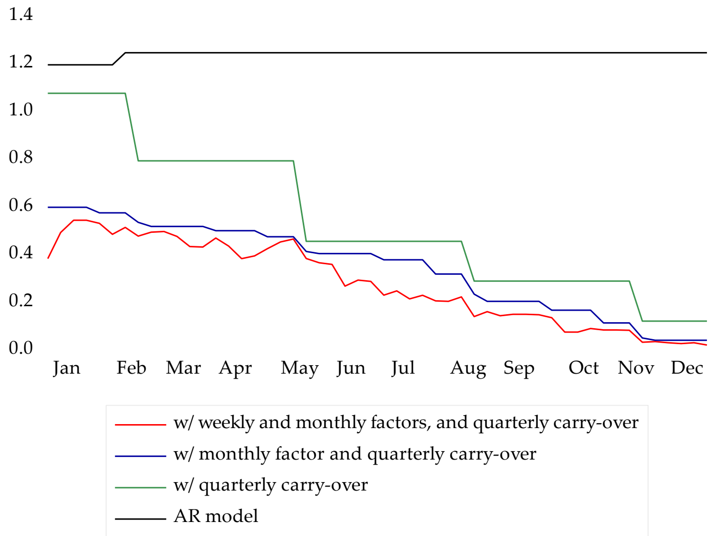


Figure A1.2. In-sample RMSE across models and weeks of the year



Annex 2: Data

Table A2.1. Description of data

	Number of series	Seasonally adjusted[1]	Sources
Quarterly dependent variable			
GDP growth	-	Yes	ECB macroeconomic projections
*Monthly regressors (**total = 718**)*			
EPU	26	No	Bloom et al. (2016) and others
Housing (e.g. new buildings)	22	Yes	National statistics, Eurostat
Car registrations	35	Yes	National statistics, ACEA[2]
Retail sales	33	Yes	National statistics, OECD
Number of employees	23	Yes	National statistics
Unemployment rates	30	Yes	National statistics, Eurostat
Industrial production	34	Yes	National statistics, Eurostat, OECD
Consumers Prices Inflation	37	Yes	National statistics, Thomson Reuters, OECD
Producers Prices Inflation	35	Yes	National statistics, Eurostat, IMF, OECD
Household confidence	33	Yes	National statistics, OECD, EU Commission
World trade	4	Yes	Centraal Plan Bureau
REER	37	No	BIS
M2 money aggregate	36	Yes	National statistics
PMI composite headline	20	Yes	IHS Markit, ISM, NBS
PMI manuf. headline	40	Yes	IHS Markit, ISM, NBS
PMI manuf. new export orders	35	Yes	IHS Markit, SIM, NBS
PMI manuf. new orders	39	Yes	IHS Markit, ISM, NBS
PMI manuf. output	39	Yes	IHS Markit, NBS
PMI manuf. delivery time	40	Yes	IHS Markit, ISM, NBS
PMI services headline	18	Yes	IHS Markit, NBS
PMI services new export orders	16	Yes	IHS Markit, NBS
PMI services new orders	6	Yes	IHS Markit, NBS
PMI services output prices	17	Yes	IHS Markit
PMI "whole" headline	13	Yes	IHS Markit
PMI "whole" new export orders	11	Yes	IHS Markit
PMI "whole" new orders	13	Yes	IHS Markit

PMI "whole" output	13	Yes	IHS Markit
PMI "whole" delivery time	13	Yes	IHS Markit
*Weekly regressors (**total = 255** – incl. 30 spreads as the difference between 3-month and 10-year rates)*			
Financial sub-set			
Stock market indices	29	No	National statistics
3-month interbank rates	30	No	National statistics
10-year sovereign yields	30	No	National statistics
NEER	31	No	JP Morgan
Other financial indices	12	No	Standard & Poor's, CBOE, MSCI
"Real" economy sub-set			
China housing indices	72	Yes	National statistics
Commodity prices	7	No	Thomson Reuters, Standard & Poor's
Trade indices	5	No	Thomson Reuters
US economy indices	9	No	Thomson Reuters

Notes: (1) the seasonal adjustment column indicates whether the series are retrieved already seasonally adjusted from the data source; (2) European Automobile Manufacturers' Association

Annex 3: Least-Angle Regression (LARS) algorithm of Efron *et al.* (2004)

Suppose the objective is to regress a target variable y on a dataset X containing a large number N of variables. The LARS algorithm starts with no variables selected.

- The first step is to identify the predictor x_j most correlated with the target variable y, then move its coefficient β_j from 0 to the direction given by its least-squares coefficient. This causes the correlation of this regressor x_j with the evolving residual $(y - \beta_j \cdot x_j)$ to decrease in absolute value. As soon as another regressor x_k has as much correlation with the evolving residual, the process is paused and x_k joins the active set.

- Then coefficients β_j and β_k are moved equiangularly in the direction of their least-squares coefficients until another predictor x_l has as much correlation with the updated evolving residual $(y - \beta_j \cdot x_j - \beta_k \cdot x_k)$.

- This procedure is continued until all predictors entered the active set, formally noted $\mathbb{A}_k$. The size of the latter increases by one at each step. After k steps, k variables are in $\mathbb{A}_k$ or in other words, the coefficients corresponding to the remaining $N - k$ predictors are set to zero in the regression.

More formally, at step k:

- Let's note $\hat{\mu}_{\mathbb{A}_k}$ the current estimate of y with the regressors corresponding to the active set $\mathbb{A}_k$.

- The vector of current correlations is $\hat{c} = X'(y - \hat{\mu}_{\mathbb{A}_k})$. By definition, the active set $\mathbb{A}_k$ is the set of indices corresponding to predictors with the highest absolute correlation noted $\hat{C} = max_j\{|\hat{c}_j|\}$, i.e. $\mathbb{A}_k = \{j : |\hat{c}_j| = \hat{C}\}$.

- The active set $\mathbb{A}_k$ defines the matrix of predictors corresponding to this set $X_{\mathbb{A}_k} = (s_j x_j)_{j \epsilon \mathbb{A}_k}$ with $s_j = sign(\hat{c}_j)$.

- $u_k = X_{\mathbb{A}_k} w_k$ is the equiangular vector: the name "least angle" arises from a geometrical interpretation of this process as u_k makes the smallest and equal angle with each of the predictors in $\mathbb{A}_k$.
  - w_k is defined as $w_k = A_{\mathbb{A}_k}({X_{\mathbb{A}_k}}' X_{\mathbb{A}_k})^{-1} 1_{\mathbb{A}_k}$ with $A_{\mathbb{A}_k} = (1'_{\mathbb{A}_k}({X_{\mathbb{A}_k}}' X_{\mathbb{A}_k})^{-1} 1_{\mathbb{A}_k})^{-1/2}$ with $1_{\mathbb{A}_k}$ a vector of ones equalling the size of $\mathbb{A}_k$.
  - We also define the inner product $a_{\mathbb{A}_k} = X' u_k$.

The next step is to move the estimation $\hat{\mu}_{\mathbb{A}_k}$ in the direction set by the equiangular vector u_k until another regressor from ${\mathbb{A}_k}^c$ (i.e. the complement of $\mathbb{A}_k$ or in other words the regressors that are not yet included in the active set) joins the active set. Formally noted, estimation will reach $\hat{\mu}_{{\mathbb{A}_k}^+} = \hat{\mu}_{\mathbb{A}_k} + \hat{\gamma} \cdot u_k$ with $\hat{\gamma}$ minimizing the following criterion:

$$(A5.1)\ \hat{\gamma} = min^{+}_{j \in \mathbb{A}_k{}^c}\left(\frac{\hat{C} - \hat{c}_j}{A_{\mathbb{A}_k} - a_j}, \frac{\hat{C} + \hat{c}_j}{A_{\mathbb{A}_k} + a_j}\right)$$

where the min^{+} indicates that the minimum is taken over only positive components of each choice of j.

The interpretation is that $\hat{\mu}_{\mathbb{A}_k}$ is moved in the direction of u_k so that $\mu_{\mathbb{A}_k}(\gamma) = \hat{\mu}_{\mathbb{A}_k} + \gamma \cdot u_k$. Then the correlations for the active set (which are all equal and have the highest absolute value among all potential predictors) all decline equally to $c_j(\gamma) = x_j' \left(y - \mu_{\mathbb{A}_k}(\gamma)\right) = \hat{c}_j - \gamma \cdot a_j$ and therefore in absolute value $\left|c_j(\gamma)\right| = \hat{C} - \gamma \cdot A_{\mathbb{A}_k}$.

Equating these two last equations provides the criterion for $\hat{\gamma}$ set in equation (A5.1). $\hat{\gamma}$ can be interpreted as the smallest positive value of γ so that a new index l joins the active set (i.e. whose absolute correlation with the residual will equal the absolute correlation of the variables in the active set). l is the minimizing index for (A5.1) and the new active set becomes $\mathbb{A}_{k+1} = \mathbb{A}_k \cup \{l\}$ and the new maximum correlation becomes $\hat{C} - \hat{\gamma} \cdot A_{\mathbb{A}_k}$

A main difference with the traditional forward stepwise algorithm is that $\hat{\gamma}$ in the updating rule is endogenously chosen in the LARS algorithm, so that it proceeds equiangularly between the variables in the active set ("least angle direction") until the next variable to be added in the active set is found. By contrast, in the forward stepwise algorithm, the updating rule is $\hat{\mu}_{k+1} = \hat{\mu}_k + \hat{\gamma} sign(\hat{c}_j) x_j$ with $\hat{\gamma} = |\hat{c}_j|$. In other terms, it updates the least squares fit to include active regressors. LARS only enters predictors only by "as much" as needed before another regressor is achieve as much correlation with the residual. This way, regressors mildly correlated with other variables already in the active set have a chance to enter – correcting the excessive parsimony of forward stepwise selection (Bai and Ng, 2008; Hastie *et al.*, 2008; Bulligan *et al.*, 2015).

Finally, Efron *et al.* (2004) show that the LARS algorithm encompasses other shrinkage methods, including LASSO (Tibshirani, 1996) and the Elastic Net (Zou and Hastie, 2005. The LASSO modification of the LARS algorithm is that if a non-zero coefficient for a regressor in the active set hits zero, then this regressor is dropped from the active set and the current joint least squares direction is recomputed. Bai and Ng (2008) also show that, in order to reformulate the Elastic Net as a LASSO problem, it is sufficient to apply a variable transformation, which can therefore be obtained through the LARS algorithm.