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Nowcasting GDP of Major Economies During the Crisis: Does Energy Matter?

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Abstract: In this article we compare the accuracy on nowcasts obtained with different models and different sets of indicators used as predictors for a set of 19 major economies. We compare the performance of mixed-frequency Bayesian VAR models, Dynamic Factor models and unrestricted MIDAS models with L1 regularization. We test different groups of commodity prices as possible predictors: energy indicators, agricultural commodities, precious metals and industrial metals prices. We find that among all the indicator groups tested energy commodities prices yield the highest average nowcasting accuracy, even though the accuracy of models utilizing all the indicators available remains slightly higher. Among all the models tested, the highest quality is yielded by Mixed-Frequency Bayesian VAR models. We also emphasize the importance of manual selection of predictors for non-diversified economies, where it can significantly improve the accuracy of nowcasts compared to the models with a wide set of predictors

Keywords: Nowcasting, Bayesian Vector Auto Regression, GDP, Oil Price.

1. INTRODUCTION

One of the significant problems with macroeconomic statistics is the publication lag: the most important macroeconomic data is often published with several month lag (or longer). This problem becomes especially crucial in circumstances such as the recent crisis, caused by the new coronavirus infection: the necessity of stimulus is evident, but the exact amount is hard to determine without all the relevant statistics. One of the possible solutions for this problem is nowcasting of macroeconomic indicators.

Nowcasting is an estimation of the current level of an indicator that is published with a significant lag and is not observable at the moment the calculations are made, using a set of indicators that are published faster. The most typical nowcasting problem is GDP nowcasting as the GDP data, on the one hand, is usually published with a several month lag after the end of the corresponding period, and on the other hand, GDP is crucial in policy making and decision making of many agents. In this paper we investigate GDP nowcasting based on a set of commodity prices and PMIs.

From a technical point of view, there are several main approaches to GDP nowcasting. First, these are coupling equations based on predicting a high-frequency series using standard methods, then aggregating it into lower frequency data and using the resulting indicator as an explanatory variable in the low-frequency equation for the indicator of interest. This approach was presented, for example, in [11], and still retains considerable popularity, see [17, 18]. Another very common class of econometric models is the so-called MIDAS (Mixed Data Sampling) mixed data frequency). This approach is based on using in the equation for a lower frequency series (for example, quarterly) as explanatory variables several values of a higher frequency series related to the current period (for example, three monthly values of another indicator related to this quarter). Depending on the specification, a number of

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restrictions on the values of the coefficients of the model can be introduced: models without restrictions are usually called unrestricted MIDAS models (U-MIDAS). Presented in [8, 9], models of this class are widely used for the nowcasting of macroeconomic indicators, see, for example, [2, 7, 14]. From technically more complex approaches, one can single out Mixed Frequency Vector Autoregression (MFVAR), based on the description of the joint dynamics of high-frequency indicators and the unobserved decomposition of low-frequency indicators into higher frequency data, see, for example, [12] or [16] in the application to nowcasting. There are also Bayesian generalizations of this approach [15].

When building a nowcasting system, one has to choose between different model types and different indicators that can be used as explanatory variables in a nowcasting model. This choice becomes especially important for tasks of building a nowcasting system for a set of countries with different structures of the economy. In this paper, we test a set of widely used nowcasting models (MIDAS, Mixed Frequency Bayesian VARs, DFM) on data for 19 major economies. We also compare different sets of operative indicators: a set of PMI indicators and several sets of world commodity prices: prices for energy commodities, metals (both precious and industrial) and agricultural commodities.

PMIs are a common choice in nowcasting and are often found to increase the nowcasting accuracy in real-time settings (see, e.g., [13] for the US and [5] for the Euro area). The most popular choice among commodity prices is oil price, see, e.g., [2,4], and our main hypothesis is in line with this choice: among all the commodity groups, prices of energy indicators (including oil and gas prices) can yield the highest nowcasting accuracy.

2. METHODS

We employ a relatively standard for nowcasting literature set of models: MIDAS (Mixed Data Sampling) models, dynamic factor models and mixed-frequency Bayesian vector autoregressions.

MIDAS models are based on the utilization of higher-frequency indicators as explanatory variables. This class of models was presented [8,9] and is widely used in nowcasting of macroeconomic indicators (see [2, 7, 14]).

In the general case, a MIDAS model assumes that

$$y_t = \sum_{j=1}^{p} \alpha_j y_{t-j} + \sum_{i=0}^{k} \sum_{j=0}^{m_i} \beta_j^{(i)} x_{tm_i - j}^{(i)} + u_t,$$

where y_t is lower-frequency data (in our case – quarterly series of GDP growth rate); $x_t^{(i)}$ - factors of higher frequency (in our case – monthly series of PMI of energy commodities prices); m_i defines the number of $x^{(i)}$ observations in one observation of dependent variable (3 months in a quarter in our case). MIDAS models also often imply restrictions on $\beta_j^{(i)}$, but in our case, we focus on unrestricted MIDAS models without autoregressive component. Instead, we use LASSO regularization so that our resulting model can be written as:

$$y_t = \beta^0 + \sum_{i=1}^{k} \sum_{j=0}^{m_i} \beta_j^{(i)} x_{tm_i - j}^{(i)} + u_t$$

with target function

$$\sum_{t=1}^{T} (y_t - \hat{y}_t)^2 + \lambda \sum_{i=1}^{k} \sum_{j=0}^{m_i} \left| \beta_j^{(i)} \right| \to \min_{\beta_j^{(i)}}.$$

Regularization for U-MIDAS models can prevent overfitting while allowing for more complex dependencies and yielding higher forecasting accuracy (see [19]).

Mixed-frequency BVARs describe the joint dynamics of variables of different frequencies in a single VAR model. They are widely used in nowcasting literature: see [15, 16] for one of the first applications, or more recent [3] shows that nowcasting performance of

MFBVARs matches the performance of state-of-the-art DFM while having a more general structure and allowing for a greater flexibility.

MFBVAR assumes that all the processes (of different observed frequencies) evolve at higher frequency (monthly in our case), but are observed at lower frequency. For the variables observed in a lower frequency we assume that observed values $y_{q,t}$ are obtained from the original monthly process $x_{q,t}$ with intra-quarterly averaging (here and further when describing MFBVAR model we follow the notation of [1])

$$y_{q,t} = \begin{cases} \frac{1}{3}(x_{q,t} + x_{q,t-1} + x_{q,t-2}), t \in \{March, June, September, December\} \\ \varnothing, else \end{cases}$$

The same scheme is used in [16] for a very similar task of short-term forecasting of macroeconomic variables, including GDP.

For the x_t vector process we assume a standard VAR(p) model

$$x_t = \phi + \Phi_1 x_{t-1} + \cdots + \Phi_p x_{t-p} + \mathrm{T}_t, \quad \mathrm{T}_t \sim \mathrm{N}(0, \Sigma),$$

where $\Phi_1,...,\Phi_p$ are coefficient matrices. By combining $x_t,...,x_{t-p}$ into a single vector z_t, we can get a companion form of VAR(p) model

$$z_t = \pi + \Pi z_{t-1} + u_t, \quad u_t \sim \mathrm{N}(0, \Omega).$$

The observation equation for the original y_t process is $y_t = M_t \Lambda z_t$, where M_t is a selection matrix (that determines at which periods quarterly indicators are observed), Λ is an aggregation matrix based on weighting scheme employed (intra-quarterly averaging in our case). Both these matrices are known and determined by the data structure and assumptions made. Π and π are coefficients of companion form VAR model.

We also utilize a Minnesota-style prior which assumes for a model written in matrix form $X = W\Gamma + E$, where

$$W = (W_1, \ldots, W_T)', \ W_t = (x'_{t-1}, \ldots, x'_{t-p}, 1)',$$

Γ is the coefficients matrix and E - errors such that

$$\mathrm{vec}(\Gamma) \mid \Sigma \sim \mathrm{N}(\mathrm{vec}(\underline{\Gamma}), \Sigma \otimes \underline{\Xi}),$$

$$\underline{\Gamma}(\underline{\gamma}) = \begin{pmatrix} \mathrm{diag}(\underline{\gamma}) & 0_{n\times[(p1)+1]} \end{pmatrix}',$$

$$\xi_i = \begin{cases} \frac{\lambda_1^2}{(l^{\lambda_3} s_r)^2}, \text{lag l of variable r, i =(l-1)n+r} \\ \lambda_4^2, i = np+1 \end{cases},$$

where $\underline{\Gamma}, \underline{\Xi}$ parameters are prior beliefs specified by the researcher, ξ_i are diagonal elements of $\underline{\Xi}$, all λ parameters control the "tightness" of the prior and are tuned when estimating a MFBVAR model, s_i^2 are the residual variances from auxiliary AR(4) models. In our case, we utilize widely-used Minnesota-style prior, where prior means for all the parameters except AR(1) parameters are chosen to be 0 and prior means for AR(1) parameters are $\underline{\gamma}$. Hence, we imply that processes for all the series analyzed are AR(1) processes until the evidence (taken from the data) is enough for the estimation procedure to make the model more complex. Priors for $\underline{\gamma}$ in our case are taken to be 0 in order not to restrict them to any given value because our target variable (GDP growth rate) is stationary. Another popular choice $\underline{\gamma} = 1$ is usually applied in non-stationary dependent variable cases.

For the error covariance matrix we assume the quite common inverse Wishart prior:

$$\Sigma \sim iW(\underline{S}, \underline{\nu})$$
$$\underline{S} = (\underline{\nu} - n - 1) diag(s_1^2, ..., s_n^2)$$
$$\underline{\nu} = n + 2$$

Where s_i^2 are the residual variances from auxiliary AR(4) models. For the calculations we use the **R** package **mfbvar** of [1].

Dynamic factor model implies that all the series observed are a combination of unobserved common factors (the number of factors is lower than the number of variables studied), that can be identified and used to make forecasts and nowcasts of indicators analyzed. The general specification of a dynamic factor model can be given by

$$y_t = \mu + \Lambda f_t + \varepsilon_t,$$

$$f_t = \sum_{i=1}^{p} A_i f_{t-i} + Bu_t, u_t \sim iid\ N(0, I_q),$$

where y_t is a vector of variables investigated, vector μ and matrix Λ are parameters to be estimated, unobserved common factors f_t are assumed to follow a VAR(p) process.

We follow two-stage estimation approach as in [10], where parameters of Λ matrix and unobserved factors f_t are estimated with principal components based on a standardized and balanced panel of explanatory variables and then re-estimated on an unbalanced set of regressors using Kalman smoothing. The resulting factors are used in the model. Estimation is performed in **R** using **nowcasting** package, [6]

3. DATA AND RESEARCH METHODOLOGY

We use the data on quarterly GDP growth rates for the period of 2001 – 2020 for the following countries: USA, Russia, China, India, Argentina, Australia, Brazil, Britain, Canada, France, Germany, Indonesia, Italy, Japan, Mexico, Saudi Arabia, Turkey, Korea, South Africa. The countries selected represent a significant part of the world GDP and in the same time belong to different geographical regions and have different structures of the economy – it can be important to test the stability of results obtained. We use 4 groups of monthly commodity prices (obtained from World Bank's Pink Sheet – [20]) as explanatory variables:

- Energy commodities (Crude oil Brent, Dubai, WTI; Coal, Australian, South African, Natural gas US, Europe; Liquefied natural gas, Japan),
- Agricultural commodities (Wheat, US SRW; Rice, Thai 5%; Maize, Palm oil, Soybeans),
- Industrial metals (Aluminum, Iron ore, Copper, Nickel),
- Precious metals (Gold, Platinum, Silver)

We also use a set of monthly PMI series for the countries presented in the sample as a benchmark

We compare the nowcasting accuracies over the last 10 points (quarters) for different groups of indicators. During the testing phase for each data point tested we restrict the sample to the information that replicates the actual nowcasting practice: all the explanatory variables for the current quarter are known (and are not known for the subsequent quarter), the indicator nowcasted is not known. We measure the accuracies using Mean Absolute Errors (MAE) for quarterly GDP growth rates

4. RESULTS AND DISCUSSION

For each country we choose the model with the lowest MAE. Tables 4.1-4.3 present the types, factor groups and MAE for the best model for each of 19 countries and the best model with MAE for the case when all the indicators were used as a reference. Accuracies in the Table 4.1 are estimated on the whole sample, in the Table 4.2 – without 2020, to measure the quality during a relatively stable period.

We see that not in all the cases the best nowcast is obtained using the bigger sample of indicators. For the countries with economies focused on a particular group of products, such as Saudi Arabia, the accuracy of nowcast using only the most appropriate group of prices is almost twofold higher than for the model with all the indicators (even though this set still includes energy commodities prices). It allows us to conclude that in at least some cases the more is not always the better and manual selection of predictors can boost the performance of the model

Table 4.1. Types of best models and their nowcasting MAE for models with one groupof factors and models with all factors, % GDP

	One group			All indicators	
	Type	Factor	MAE	Type	MAE
USA	MIDAS_L1	IndMetal	1.56	MFBVAR	1.77
Russia	DFM	PMI	1.74	MIDAS_L1	1.60
China	MIDAS_L1	PrecMetal	1.86	MFBVAR	1.71
India	MIDAS_L1	Energy	3.89	DFM	4.34
Argentina	MFBVAR	Energy	3.85	MFBVAR	2.64
Australia	MIDAS_L1	PMI	1.44	MIDAS_L1	1.35
Brazil	DFM	PMI	2.04	MFBVAR	1.48
Britain	MIDAS_L1	PMI	3.17	MIDAS_L1	2.96
Canada	MFBVAR	PMI	1.13	MFBVAR	1.49
France	MIDAS_L1	IndMetal	2.82	MFBVAR	3.04
Germany	DFM	PMI	1.79	MFBVAR	1.15
Indonesia	MIDAS_L1	PrecMetal	1.30	MIDAS_L1	1.45
Italy	DFM	PMI	2.60	MIDAS_L1	2.79
Japan	MIDAS_L1	IndMetal	1.63	MFBVAR	1.55
Mexico	MFBVAR	Energy	3.16	MFBVAR	2.79
Saudi Arabia	MFBVAR	Energy	1.19	DFM	2.26
Turkey	MFBVAR	Energy	2.00	MFBVAR	2.97
Korea	MFBVAR	IndMetal	1.31	MFBVAR	0.96
South Africa	MIDAS_L1	Agriculture	0.57	MIDAS_L1	0.60

The first table answers the question of the best way to predict the economic growth of each of the countries, especially in the specific conditions of 2020. The first thing to pay attention to is the question of whether one group of factors can be distinguished, or whether models with the entire set of variables work best. Moreover, the group of those countries for which models with the entire set of indicators work better includes, for example, Russia, China, Germany and the United Kingdom.

On the other hand, for example, for countries such as the United States, India and France, it is possible to single out one group of variables that work best. We also see that, among all the indicator groups, the most frequent “winners” are energy commodity prices and PMI. These results hold even for the more stable sample without 2020.

Table 4.2. Types of best models and their nowcasting MAE for models with one group of factors and models with all factors without 2020, % GDP

	One group			All indicators	
	Type	Factor	MAE	Type	MAE
USA	MIDAS_L1	IndMetal	0.39	MFBVAR	0.40
Russia	MFBVAR	Agriculture	0.58	MIDAS_L1	0.69
China	MIDAS_L1	PrecMetal	0.37	MIDAS_L1	1.40
India	MFBVAR	Agriculture	0.57	MFBVAR	0.66
Argentina	MFBVAR	Energy	2.40	MFBVAR	2.46
Australia	MFBVAR	PMI	0.41	MFBVAR	0.34
Brazil	MFBVAR	IndMetal	0.49	MIDAS_L1	0.47
Britain	MIDAS_L1	PMI	0.52	MIDAS_L1	0.49
Canada	MIDAS_L1	PMI	0.44	MFBVAR	0.63
France	MIDAS_L1	IndMetal	0.34	MIDAS_L1	0.53
Germany	DFM	PMI	0.68	MFBVAR	0.68
Indonesia	MIDAS_L1	PrecMetal	0.21	MIDAS_L1	0.23
Italy	MIDAS_L1	Energy	0.52	MIDAS_L1	0.41
Japan	MIDAS_L1	IndMetal	0.63	MIDAS_L1	0.68
Mexico	MFBVAR	PMI	0.84	MFBVAR	1.15
Saudi Arabia	MFBVAR	Energy	0.88	DFM	1.38
Turkey	MFBVAR	Energy	2.03	MFBVAR	2.49
Korea	MFBVAR	PMI	0.42	MFBVAR	0.46
South Africa	MIDAS_L1	Agriculture	0.43	MIDAS_L1	0.70

Comparing the results from the two previous tables is the most interesting. This approach actually allows us to draw meaningful conclusions about how radically the mechanisms that determine a significant part of the economic growth of the world's largest economies have changed. All countries can be divided into three groups depending on what composition of factors is used, and whether this composition of factors changes in models with and without 2020. The first group of countries includes Australia, Brazil, the UK and Germany. The most working models for these countries both without and taking into account 2020 include all variables.

The second group of countries includes the USA, Canada, France, Indonesia, Saudi Arabia, Turkey and South Africa. The most working models for these countries contain only one group of variables, regardless of whether 2020 is included in the models. For the US and France, industrial metal prices are the best leading indicators. For Saudi Arabia and Turkey, prices for energy products. That is, a factor that is a good leading indicator can be both the main export product and the product on whose import the economy is critically dependent.

Finally, the third group includes Russia, China, India, Argentina, Italy, Japan, Mexico and Korea. For them, models with the addition of data for 2020 differ significantly from models without this period. Almost all of these countries (the only exceptions are Italy and India, which at different times experienced a very strong shock from the spread of the coronavirus) have the same trend. With the addition of the 2020 data, the model that used only one group of indicators changes to a model that includes all groups of factors. It seems to us that this is a rather significant effect associated with the crisis events of 2020. During this period, the interrelationships in the economy become more complex, and it is impossible to say in advance which variable will make the greatest contribution. Therefore, models that take into account all the analyzed factors begin to work more accurately.

Table 4.3 present the mean MAE for all the models and predictor groups with and without 2020. In both cases the best nowcasting quality is obtained using MFBVAR and in both cases the best indicator group is energy commodities prices. However, for the whole sample MFBVAR with all the indicators performs better.

Table 4.3. Average errors (MAE) across all country models, % GDP

	Energy	PMI	PrecMetal	IndMetal	Agriculture	All indicators
All time						
MFBVAR	**2.66**	3.34	3.13	2.76	4.38	**2.37**
DFM	2.96	2.74	3.10	3.03	3.07	3.02
MIDAS_L1	3.03	3.30	3.23	3.36	3.23	2.55
Without 2020						
MFBVAR	**1.14**	1.26	1.29	1.16	1.23	1.17
DFM	1.63	1.54	1.66	1.61	1.64	1.62
MIDAS_L1	1.63	1.94	2.12	1.95	1.70	1.17

5. CONCLUSION

In this article we compare the accuracy on nowcasts obtained with different models and different sets of indicators used as predictors for a set of 19 major economies. We compare the performance of mixed-frequency Bayesian VAR models, Dynamic Factor models and unrestricted MIDAS models with L1 regularization. We test different groups of commodity prices as possible predictors: energy indicators, agricultural commodities, precious metals and industrial metals prices.

We found that energy really matters in nowcasting tasks: especially for non-diversified economies and during stable periods of time. Energy commodities prices used as predictors for nowcasting models yield lower mean nowcasting errors than any other group of indicators, including widely-used PMIs. We also found that mixed-frequency Bayesian VARs tend to have the highest accuracy in most of the cases analyzed.

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