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Nowcasting the Real GDP Growth of Rwanda

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Abstract

The main contribution of this paper is to develop a new set of real Gross Domestic Product (GDP) nowcasting tools, namely, the Bridge equations, Mixed Frequency Data Sampling (MIDAS) models and the combined forecasting technique, and to compare their performance against the benchmark models currently used at the National Bank of Rwanda (NBR), namely, the Autoregressive Moving Average (ARMA) models and the Dynamic Factors Model (DFM). Our empirical findings indicate that all the three new nowcasting models outperform the benchmark models, with the bridge equations taking the lead. We therefore recommend the inclusion of MIDAS, Bridge and combined forecasting models as part of the GDP nowcasting system for the NBR, to complement the existing models as this can help to improve the forecast accuracy.

KeyWords: Gross Domestic Product, Nowcasting, Mixed Frequency Data Sampling, Forecast combination, Bridge equations.

JEL Classification Numbers: C22, C52, C53, E37.

1. Introduction

Public policy making such as in monetary policy or public finance, depends on information on the past, current, and near-future conditions of the economy as a whole. However, data on many macro-economic indicators are published with substantial delays. This is especially true for the Gross Domestic product, a key macro-economic indicator, whose data collection and processing takes a while and is published almost three months after the referenced quarter. This has raised the need to come up with economic and statistical models that use information that has been published earlier to predict GDP for the real-time perception of the economy's state, which is known as nowcasting.

Nowcasting has been defined as the prediction of the very recent, current, and near-future of the concept of interest (Marcellino et al., 2008; Blanco et al., 2017; Habimana et al., 2020). It is basically exploiting all possible available hard and/or soft information[1] that are published before the target variable, GDP in our case, and using them to make its early predictions. A challenge in using other indicators to predict GDP, is that they too are published on different dates, such that the last observation is different from one series to another, hence making some indicators have missing numbers. Such a database would then be described as being 'jagged/ragged edge.' Another challenge is that different indicators have different frequencies, e.g., some are released at daily, monthly, or quarterly frequencies. Different models of nowcasting treat these data issues differently.

There are many models used to nowcast. Examples of commonly used approaches are the bridge equations, Dynamic Factor Models (DFM), Mixed-Data Sampling (MIDAS), and Combined Forecasting Approaches. The differences in these approaches stem from how they treat the raggedness of the data, the different frequencies, different data ranges considered useful, and how they model the relationship between the different variables and GDP (Bell et al., 2014). The task of a model analyst is to find out which model(s) make(s) the most accurate prediction of GDP.

Monetary policy decision-making in Rwanda, like other

[1] Soft Information from surveys

public policies, relies on a timely assessment of past, present, and future economic conditions. Assessments of current economic conditions are often complicated by the delay of the GDP data which is usually published in the third month after the end of the reference quarter. This leads to lack of real time GDP data to be used to produce macroeconomic projections in the forecasting round of the reference quarter to better inform the monetary policy committee (MPC). Habimana et al. (2020), Aiolf et al. (2010) and Vlcek et al. (2020) list a publishing schedule for different indicators of varying frequencies that have been used to forecast the Rwandan GDP.

In this context, the National Bank of Rwanda has been producing the GDP nowcast since the establishment of the price-based monetary policy, and the results are incorporated into the Quarterly Projection Model (QPM) to help provide an accurate macroeconomic forecasts, especially regarding the future path of inflation.

The NBR has uses the DFM model to provide the GDP nowcast (Karangwa and Mwenese, 2015). However, the nowcast experience at NBR has been recently characterized by large forecast errors, and according to Mancuso and Werner (2013), significant deviations of forecasts from actuals can lead to a negative impact on economic performance through misguided policy decisions. Thus, the goal of this study is to improve the accuracy of the Real GDP growth nowcast produced by National Bank of Rwanda (NBR), by exploring other nowcasting models.

Apart from the DFM model, which is one of the most used models for forecasting current GDP, this paper will also examine other commonly used models; the bridge equations (B.E.) and MIDAS models whose accuracy has been different for different countries when compared to each other (Kunovac and Špalat, 2014; Bańbura et al., 2013; Kuzin et al., 2009).

This study also adopts the forecast combination technique which is suggested to improve the forecast accuracy by minimizing forecasting errors of individual nowcasting models (Hibon and Evgeniou, 2005; Kapetanios et al., 2008; Aiolf et al., 2010). These bridge equation, MIDAS and forecast combination techniques are compared to the DFM and ARMA models, with the latter two representing the benchmark models.

This paper contributes to a growing literature on GDP nowcasting in Rwanda by examining the performance of the Bridge equation, mixed-data sampling (MIDAS) and the Dynamic factor model (DFM), as well as the combination forecasts of the models.

This paper is divided into five sections, the first being the introduction. Section two presents a description of the forecasting methods being used while the third section discusses the data and empirical results. Section four concludes.

2. Approaches to Nowcast GDP

2.1. The bridge equations.

This nowcast approach is used to estimate many small forecasts and then aggregate them for the final value of the target variable. It is said to be one of the earlier adopted methods of nowcasting using mixed frequency data. It is said to be iterative since it requires several steps in order to forecast the dependent variable. The first step is to deal with the missing observations of the predictor variables by forecasting them using models such as A.R., VAR, and ARMA to fill in the gaps for the remaining projection period of the dependent variable (Schumacher, 2014; Foroni and Marcellino, 2013; Allan et al., 2019).

The second step is aggregating or interpolating the predicting indicators in order to have the same frequency as the dependent variable. Aggregation is a technique for adjusting the high-frequency indicator to match the low-frequency dependent variable. How to aggregate will depend on whether the variable is a stock or a flow. Typically, an average is used for stock variables and a sum for flow variables. Another option for aggregating both flow and stock variables is by using the latest available value for the high-frequency variable. Interpolation, which is rarely used, is adjusting the low-frequency variable to the high-frequency one (Schumacher, 2014).

After aggregation, the third step is to use the aggregated values as regressors in the bridge equation, which has the structure of a simple OLS equation. The variables used may not be based on causal relation but on the timeliness of the updated information. They can be selected using information criterion, RMSE performance, or Bayesian Model Averaging Performance (Foroni and Marcellino, 2013).

The bridge model can be represented as follows;

$$y_{t_q} = a + \sum_{i=n}^{l} \phi y_{t-1\ldots t-n_q} + \sum_{i=1}^{l} \delta_i(L) x_{it_q} + u_{t_q} \quad (1)$$

Where $\delta_i(L)$ is a lag polynomial, and x_{it_q} are selected monthly indicators at a quarterly level q. The equation also contains an autoregressive term $\phi y_{t-1\ldots t-n}$ whose lag order, l, can be determined by information criteria (Andersson and den Reijer, 2015).

Each indicator will have its own bridge equation and, therefore, its own forecast of the dependent variable. The final step is then to either find the mean of all projected values or select the best models by selecting them using RMSE.

2.2. The Mixed-Data Sampling (MIDAS) Model

The main feature of this model is that it forecasts using predictors in their original frequencies, whether different, hence its name, and regardless of whether they are jagged or not. MIDAS approach is a more direct approach where the dependent (forecasted) variable is associated with the indicator variables and their lags without aggregation to match the frequency of all variables. In addition, another key factor that distinguishes the MIDAS model is its attempt to use as few parameters as possible(parsimony) through a polynomial which makes it easier to interpret and understand (Foroni and Marcellino, 2013; Schumacher, 2014; Chikamatsu et al., 2018; Allan et al., 2019; Habimana et al., 2020; Laine and Lindblad, 2021).

Laine and Lindblad (2021) illustrate the structure of a simple MIDAS model, which has one explanatory variable;

$$y_t = \beta_0 + \beta_1 \sum_{h=0}^{l} \phi_h x_{tm-h} + u_t \tag{2}$$

where y_t is the dependent low-frequency variable and x_{tm-h} the high-frequency variable. m is the number of times the high-frequency variable is published by the time the low-frequency variable is published. β_1 shows the association between the predictor and predicted variables. l is the number of lags of the explanatory variable included in the model.

ϕ_h is the function that helps achieve parsimony in the model. It is a polynomial that enables the model to consider and weigh a large number of lags for the high-frequency explanatory variable and its lags. Some lag polynomials that can be used are the Exponential Almond lag polynomial or the smooth lag polynomial, which allow flexible weighting schemes that can even be hump-shaped or decaying (Laine and Lindblad, 2021; Schumacher, 2014). This beats the weighting done by the bridge equation, which implicitly places equal weight, through aggregation, on recent and past values or on more volatile and less volatile periods on explanatory variable observations, yet these make more sense to be weighted differently so as not to lose important information (Allan et al., 2019).

An unrestricted-MIDAS(U-MIDAS) model would be used in the case that the lags included are not so many, such that every lag would have its own regression parameter. Other forms of the MIDAS equation have been detailed by Foroni and Marcellino (2013).

2.3. Dynamic Factor Model (DFM)

Nowcasts have also been estimated by dynamic factor models. This is a dimension reduction technique that summarizes the sources of variation among variables. The behavior of a large number of variables can thus be accounted for by a few unobserved factors due to the high degree of co-movement among them, which is the case for many macroeconomic variables (Doz and Fuleky, 2019; Blanco et al., 2017; Bańbura et al., 2013). It is also used for mixed frequency and jagged data without aggregation.

Each independent variable x_{it} can be illustrated in two parts as follows Doz and Fuleky (2019);

$$x_{it} = \lambda'_i f_t + \epsilon_{it} \tag{3}$$

In the first part, f_t is the unobserved common component in the variables, while λ'_i is a $r \times 1$ vector. The second part, ε_{it}, is an idiosyncratic component that has variations/features specific to each indicator. $\varepsilon_{it} = e_{it} + u_i$, where u_i=the mean of x_i. (Doz and Fuleky, 2019; Andersson and den Reijer, 2015).

The factors are estimated either by the Kalman filter or the Principal Component Analysis (PCA). In DFM models, missing observations due to jaggedness or mixed frequencies are considered to be missing randomly. The Kalman filter handles the missing values by:

”...either allowing the measurement equation to vary depending on what data are available at a given time or by including proxy value for the missing observation while adjusting the model so that the Kalman filter places no weight on the missing observation” (Doz and Fuleky, 2019).

In order to estimate the factors using the PCA, the missing variables have to be imputed using the Expectation-Maximization (E.M.)[2] algorithm (Kunovac and Špalat, 2014; Doz and Fuleky, 2019). To handle missing observations and for other types of factor models. Thus, these two features of DFM analysis enable forecasting for mixed frequency and jagged edge data.

The factor estimates will then be aggregated, and if small enough, they will be regressed against the key dependent variable using a standard regression. It will be assumed that shocks to these factors would represent a shock to the aggregate variable.

2.4. Combined forecasting model

Analysts are increasingly recommending the use of forecast combinations as they provide more accurate forecasts rather than choosing and using one model. Single models might perform well in some periods and not in some. Structural breaks affect their efficacy (Blanco et al., 2017; Chikamatsu et al., 2018).

[2]A detailed account on the use of E. M is given in Doz and Fuleky (2019)

In the process of using only one model, a lot of potentially useful information is not used in another model, and since we have complicated markets, it is beneficial to include as much information as possible. A combined forecast will also be able to capture distinct features of different models, which normally use different forecasting techniques (Mancuso and Werner, 2013).

A lot of studies that have used single approaches and combined them have unanimously concluded lower forecast errors when the latter approach is used (Galli et al., 2019; Blanco et al., 2017; Lundberg, 2017).

Linear representation of forecasts combination can be written as follows (Chikamatsu et al., 2018);

$$Y_t = \sum_{j=1}^{N} w_{j,t} XY_{j,t} \tag{4}$$

where $w_{j,t}$ is the weight applied to the jth forecast model in period t.

Different weighting schemes have been suggested by different analysts. For example, the system for averaging models (SAM) by Lundberg (2017), where the current weights of predictions are based on their historical performance in predicting accurately. Hibon and Evgeniou (2005) use simple averages for their forecast combinations, meaning equal weight for all. Mancuso and Werner (2013) also describe subjective decision-making using the Delphi method or selecting the best experts for the intuitive selection of models.

3. Empirical Application

3.1. Data

The data used for nowcasting the real GDP growth consist of domestic and foreign variables. The domestic variables are high frequency indicators that can be related to the expenditure approach of the GDP. These indicators are the total turnovers of industry and services sectors that can proxy the consumption, credit to private sector and domestic demand of cement representing the investment and external trade data (exports and imports) for export and imports GDP components. We include also production data for the industry sector, which are the index of industrial production and the electricity.

For the foreign variables, guided by the QPM Vlcek et al. (2020), we collect data on real GDP growth of US and Eurozone as well as purchasing manager index of those economic regions.

In total all these variables amount to 85 variables. To choose which variables to use in the nowcasting models, we compute their correlation with GDP. But, before that, we have seasonally adjusted the data and log differenced them to ensure their stationarity.

Table 1 in appendix show the indicators we used and table 2 indicates the correlation of each variable with GDP. We chose the variables that have a relatively high correlation with the GDP (above 50 percent) to be used in the nowcasting process. The chosen variables are 59.

3.2. Estimation procedure

An individual Bridge and MIDAS equation is estimated for each indicator following the selection of the variables. The Root Mean Square Error (RMSE) is then calculated in order to compare models to benchmark models and select the top model.

3.3. Evaluation method

To check the forecast accuracy of the nowcasting models, we compare the Root Mean Square Error (RMSE) of each model with the RMSE of the Benchmark model.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T} (y_t - \widehat{y_t})^2}{T}} \tag{5}$$

where y_t and $\widehat{y_t}$ are the actual and forecast values of GDP growth and T is the total number of forecasts.

The benchmark models consist of ARMA and the dynamic factor model (DFM). The latter is the first nowcasting model used by NBR (Karangwa and Mwenese, 2015). For ARMA model, we find the ARMA (1, 0) to be the best model (see, in appendix table 2 and 3 for estimation results).

3.4. Empirical Results and Discussion

In this section, we evaluate the forecasting performance of each indicator the outcome resulting from univariate autoregressive distributed lag (ARDL) model estimation under both bridge and MIDAS models framework. First, we rank the predictive ability of each model and compare them with the forecast performance of the AR1 model. Afterward, models with lower RMSE relative to the AR1 are combined and the combined forecast is compared to the DFM model predictive ability.

We examine the out-of-sample performance of the nowcasting models during 2019Q1 to 2022Q1. This evaluation is done for the nowcast of GDP as total and the bottom-up approach, where we aggregate the nowcast of agriculture and non-agriculture GDP.

3.4.1. Total GDP

We start by selecting the best set of indicators from both the Bridge equation and MIDAS estimation. We select the all indicators' equation that presents a lower

RMSE relative to the main benchmark model. The results shown in figure 1 indicate that both the Bridge and the Midas equations outperform the AR1 model. These findings corroborate with other empirical results indicating the outperformance of Bridge equation and Mixed data sampling technique over the ARMA model (Habimana et al., 2020; Abdić et al., 2020; Feldkircher et al., 2015). For a more accurate model, we select the indicators whose equation has a smaller RMSE than the RMSE of the weighted average forecast of all indicators.

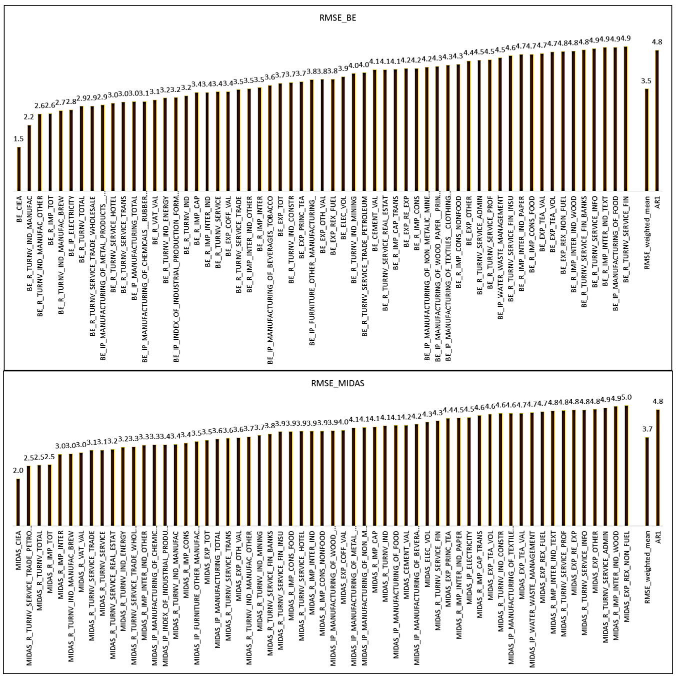

Figure 1: RMSE of all indicators models from Bridge andMIDAS estimations

The selected indicators are shown in table 3. This process will always be based on the ranking of the RMSE; hence the indicators in this group are subject to change given their nowcasting performance.

The comparison of the forecast performance of the bridge equation and MIDAS of the final set of indicators indicate that the Bridge equation and MIDAS equations perform well against the benchmark models: AR1 and dynamic factor model (DFM), as indicated in figure 2.

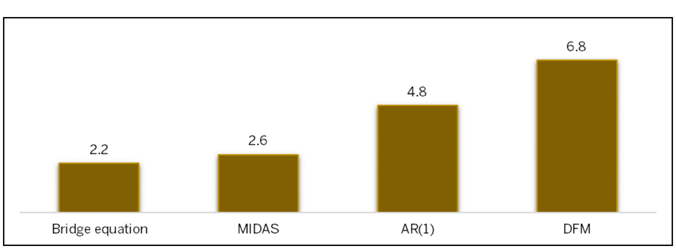

Figure 2: Comparison of best indicators bridge equation and MIDAS against the benchmark models

Table 1: Best performing indicators

Bridge Equation	**MIDAS**
CIEA	CIEA
Turnovers of manufacturing industries	Petroleum services turnovers
Turnovers of other manufacturing industries	Total turnovers
Total imports	Total imports
Turnovers of brewery industries	Intermediate goods imports
Index of industrial production of electricity	Turnovers of brewery industries
Total turnovers	VAT
Turnovers for wholesale and retail trade	Trade services turnovers
Index of industrial production of metal, machinery and equipment	Services 'sector's turnovers
Turnovers for hotels and restaurants	Real estate turnovers
Transport services turnovers	Energy sector turnovers
Index of industrial production of all manufacturing industries	Turnovers for wholesale and retail trade
Index of industrial production of chemicals, rubber, and plastic	Other industrial products intermediate goods imports
VAT	Index of industrial production of chemicals, rubber, and plastic
Energy sector turnovers	index of industrial production
Index of industrial production	Turnovers of manufacturing industries
Turnovers for industry sector	Consumer goods imports
Capital goods imports	Index of industrial production of furniture and other manufacturing industries
Industrial products intermediate goods imports	Total exports
Services 'sector's turnovers	Index of industrial production of all manufacturing industries
Value of coffee exports	Transport services turnovers
	Other exports

3.4.2. Bottom-up approach

This approach forecasts the agriculture and the rest separately, and GDP would be the sum of these two components. The bridge equation and Midas produce the nowcast for the non-agriculture sector, while the forecast of the agriculture sector is based on ARMA as the existing high-frequency indicators are related to the activities of industry and services sectors.

The agriculture sector was found to follow an autoregressive and moving average of order one after testing ARMA models and observing the Akaike, Swharz, and Hannan-Quin information criteria. We also found that the forecast for agriculture growth is better than the naïve model forecast[3], based on their RMSE, which are 2.1 (ARMA) and 2.3 (Naïve model)

For the non-agriculture sector, we apply the same procedure as on total GDP, where we first select the best indicators (see appendix figure 1 and table 5), and we produce a combined nowcast from the outcome of these indicators' equations, which is compared with the benchmark models.

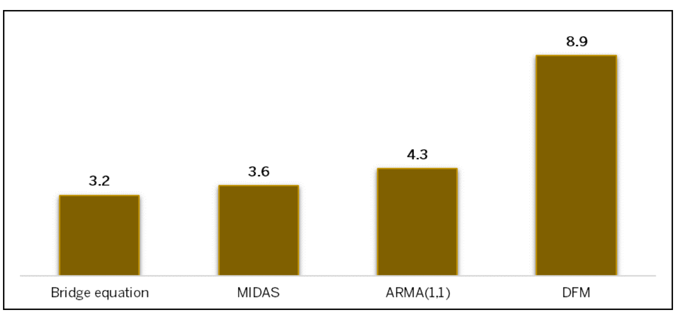

Figure 3: Comparison of best indicators bridge equation and MIDAS against the benchmark models for the Non-agriculture sector

The RMSEs in figure 3 show that the Bridge equation and MIDAS again outperform the Benchmark models and the order of performance is the same as for the nowcast of total GDP.

The aggregation of agriculture and non-agriculture 'sectors' nowcast yield a GDP nowcast that is also better than the results from the benchmark models, as shown in figure 4. However, the performance of the bottom-up approach has a lower performance than the nowcast of total GDP; but this approach has the advantage of providing room to add information or judgment for the agriculture sector, which could improve the overall nowcast performance for the concerned period.

To sum up, these results indicated that the Bridge equation and the MIDAS techniques perform better in nowcasting GDP for Rwanda compared to the ARMA model and the dynamic factor model.

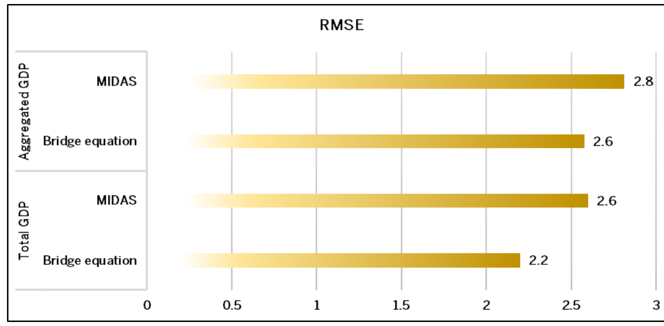

Figure 4: Nowcast performance for bottom-up and total GDP approaches

The Bridge equation technique came out as the top performer, but since no single technique can consistently produce best forecast, as observed by Feldkircher et al. (2015), the most efficient technique is to combine the outcome of all the models. This strategy was also used by Kalisa and Uwase (2018) and Habimana et al. (2020) and was found to perform relatively well than considering solely one technique of nowcasting GDP.

Therefore, we tested the performance of a combined forecast of all the models. We observe that the outcome of the combination of all model has a higher RMSE than the Bridge equation. This demonstrates that the Bridge equation outperformed the other models in the evaluation sample.

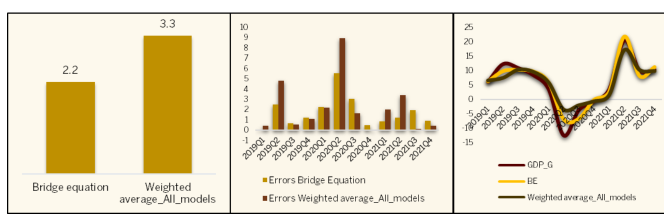

Figure 5: Bridge equation and combined forecast evaluation

When we look at the evolution of errors for the two forecasting approaches, we note that the combination forecast has a lower absolute error than the Bridge equation in seven out of twelve quarters. This implies that, during the nowcasting exercise, all models and their combinations should be evaluated, and the outcome with the smallest error should be used for the real GDP nowcast for that period.

4. Conclusion

Economic policy decision making, especially monetary policy, depends on the real-time assessment of the current and future macroeconomic conditions. Since the MPC

[3] Using the last period values as the forecast for the next period.

of the NBR convenes every quarter to decide on policy actions aimed at influencing the future path of the economy, especially aimed at fulfilling its main mandate of price stability, such real time assessment of the economy is important. Unfortunately, some key economic indicators such as GDP are often released with a lag of several weeks after the end of the period of interest. Thus, the nowcasting econometric technique offers a remedy to this challenge.

In this paper, we used this technique with the objective of improving the accuracy of the NBR nowcasting system. We evaluated the out of sample nowcasting performance of Bridge equations and mixed data sampling (MIDAS) technique against the dynamic factor and ARMA models. The findings evidenced that these two types of nowcasting technique outperformed the benchmark models and the combination of all the models also was found to improve the accuracy of the GDP nowcast. Therefore, we recommend upgrading the existing NBR nowcasting system by including the Bridge equations and MIDAS class of models and using the all models combination in the GDP nowcasting exercise. In addition, all models and the combined forecast must be evaluated in order to select the outcome with the smallest error for the relevant period. Furthermore, in pursuit of a more accurate GDP nowcast, we recommend a continuous exploration of new data and indicators, as well as other nowcasting alternatives.

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Table 2: Series used in the nowcasting models

Indicator	Source	Frequency	Publication lags (months)
Real GDP growth	NISR	Q	3
CIEA	NBR	M	1
Cement	CIMERWA, PRIME CEMENT and RRA	M	1
Electricity	REG	M	1
Coffee exports	NAEB	M	1
Tea exports	NAEB	M	1
Mining exports	RRA	M	1
Other exports	RRA	M	1
Index of Industrial Production (IP)			
IP Mining & quarrying	NISR	M	1
IP Manufacturing of food	NISR	M	1
IP Manufacturing of beverages & tobacco	NISR	M	1
IP Manufacturing of textiles, clothing & leather goods	NISR	M	1
IP Manufacturing of wood & paper; printing	NISR	M	1
IP Manufacturing of chemicals, rubber & plastic products	NISR	M	1
IP Manufacturing of non-metalic mineral products	NISR	M	1
IP Manufacturing of metal products, machinery & equipment	NISR	M	1
IP Furniture & other manufacturing	NISR	M	1
IP Manufacturing Total	NISR	M	1
IP Electricity	NISR	M	1
IP Water & waste management	NISR	M	1
Overall Index (IIP)	NISR	M	1
IMPORTS			
Total Imports	RRA	M	1
Capital imports	RRA	M	1
Capital imports_transport materials	RRA	M	1
Capital imports_Non-transport materials	RRA	M	2
Consumer goods imports_food	RRA	M	1
Consumer goods imports_Non-food	RRA	M	1
Consumer goods imports	RRA	M	1
Energy imports_Non-petroleum	RRA	M	1
Energy imports_Petroleum	RRA	M	1
Energy imports	RRA	M	1
Intermediary goods imports_ construction materials	RRA	M	1
Intermediary goods imports_Fertilizers	RRA	M	1
Intermediary goods imports_Chemicals	RRA	M	1
Intermediary goods imports_food	RRA	M	1
Intermediary goods imports_metals	RRA	M	1
Intermediary goods imports_other industrial products	RRA	M	1
Intermediary goods imports_paper	RRA	M	1
Intermediary goods imports_industrial products	RRA	M	1
Intermediary goods imports_textile	RRA	M	1
Intermediary goods imports_wood	RRA	M	1
Intermediary goods imports_other intermediary goods	RRA	M	1
Intermediary goods imports	RRA	M	1

Table 3: Series used in the nowcasting models

Indicator	Source	Frequency	Publication lags (months)
TURNOVERS (TURNV)			
TURNV_Agriculture	RRA	M	1
TURNV_construction	RRA	M	1
TURNV_energy and water	RRA	M	1
TURNV_breweries	RRA	M	1
TURNV_other manufacturing (other than brewery)	RRA	M	1
TURNV_total manuacturing	RRA	M	1
TURNV_mining	RRA	M	1
TURNV_total industry sector	RRA	M	1
TURNV_total Services sector	RRA	M	1
TURNV_Wholesale and Retail trade; Repair of motor vehicles and motorcycles	RRA	M	1
TURNV_ Wholesale and retail trade	RRA	M	1
TURNV_Petroleum Distributors	RRA	M	1
TURNV_Transport and storage	RRA	M	1
TURNV_Hotels and Restaurants	RRA	M	1
TURNV_Information and Communication	RRA	M	1
TURNV_Financial and insurance	RRA	M	1
TURNV_Banks	RRA	M	1
TURNV_Insurance companies	RRA	M	1
TURNV_Real Estate	RRA	M	1
TURNV_Professional, Scientific and Technical services	RRA	M	1
TURNV_Administrative and Support Services	RRA	M	1
TURNV_Public Sector	RRA	M	1
TURNV_Education	RRA	M	1
TURNV_Human Health and Social Work	RRA	M	1
TURNV_Arts, Entertainment and Recreation	RRA	M	1
TURNV_Other Services	RRA	M	1
TURNV_TOTAL	RRA	M	1
VAT	RRA	M	1
US GDP	Federal Reserve Economic Data	Q	1
EUROZONE GDP	Federal Reserve Economic Data	Q	1
US PMI	Bloomberg	M	1
EUROZONE PMI	Bloomberg	M	1

Table 4: Indicators correlation with GDP

Variable	IP_ELECTRICITY	IP_FURNITURE_OTHER_MANUFACTURING	IP_INDEX_OF_INDUSTRIAL_PRODUCTION_FORMAL	IP_MANUFACTURING_OF_BEVERAG
Correlation	99.2	94.8	98	86.2
Variable	IP_MANUFACTURING_OF_TEXTILES_CLOTHING	IP_MANUFACTURING_OF_WOOD_PAPER_PRINTING	IP_MANUFACTURING_TOTAL	IP_MINING_QUARRYING
Correlation	90.9	90.8	97.2	15
Variable	ELEC_VAL	ELEC_VOL	R_CPS	R_IMP_CAP
Correlation	97.1	98.3	96.7	58.6
Variable	R_IMP_ENER_NON_PETROLEUM	R_IMP_ENER_PETROLEUM	R_IMP_ENERG	R_IMP_INTER
Correlation	48.9	44.7	46.7	79
Variable	R_IMP_INTER_IND_FOOD	R_IMP_INTER_IND_METAL	R_IMP_INTER_IND_OTHER	R_IMP_INTER_IND_PAPER
Correlation	36.9	-27.7	88.6	86.7
Variable	R_IMP_TRANS_NON_TRANS	R_TURNV_AGR	R_TURNV_IND	R_TURNV_IND_CONSTR
Correlation	41	37.1	99	92.1
Variable	R_TURNV_IND_MINING	R_TURNV_SERVICE	R_TURNV_SERVICE_ADMIN	R_TURNV_SERVICE_ARTS
Correlation	79	98	89.4	23.5
Variable	R_TURNV_SERVICE_HEALTH	R_TURNV_SERVICE_HOTEL	R_TURNV_SERVICE_INFO	R_TURNV_SERVICE_OTH
Correlation	41.9	56.3	84.9	-60.7
Variable	R_TURNV_SERVICE_TRADE_RETAIL	R_TURNV_SERVICE_TRADE_WHOLESALE	R_TURNV_SERVICE_TRANS	R_TURNV_TOTAL
Correlation	78.3	96.8	92.9	98.7
Variable	EXP_MINING_VOL	EXP_OTH_VAL	EXP_OTHER	EXP_PRINC
Correlation	-5.1	79.3	73.4	16.3
Variable	EXP_PRINC_PYRETHRUM	EXP_PRINC_TEA	EXP_PRINC_WOLFRAM	EXP_RE_EXP
Correlation	1.7	85.3	39.4	96.9
Variable	EXP_TOT	USGDP	EuroGDP	US_PMI
Correlation	87.7	43.6	45.4	11.2
Variable	IP_MANUFACTURING_OF_CHEMICALS_RUBBER_PLASTIC	IP_MANUFACTURING_OF_NON_METALLIC	IP_MANUFACTURING_OF_METAL_PRODUCTS	IP_MANUFACTURING_OF_MACHINERY
Correlation	93.6	87.9	92.8	93.1
Variable	IP_WATER_WASTE_MANAGEMENT	CEMENT_VAL	CEMENT_VOL	CIEA
Correlation	95.4	83.9	30.9	99.2
Variable	R_IMP_CAP_TRANS	R_IMP_CONS	R_IMP_CONS_FOOD	R_IMP_CONS_NONFOOD
Correlation	67	83.4	79.9	51
Variable	R_IMP_INTER_CONSTR	R_IMP_INTER_FERT	R_IMP_INTER_IND	R_IMP_INTER_IND_CHEM
Correlation	17.4	24.5	86.5	24
Variable	R_IMP_INTER_IND_TEXT	R_IMP_INTER_IND_WOOD	R_IMP_INTER_OTHER	R_IMP_TOT
Correlation	83.9	62.4	30.2	89.5
Variable	R_TURNV_IND_ENERGY	R_TURNV_IND_MANUFAC	R_TURNV_IND_MANUFAC_BEV	R_TURNV_IND_MANUFAC_OTHER
Correlation	97.1	99	97.4	98.7
Variable	R_TURNV_SERVICE_EDUC	R_TURNV_SERVICE_FIN	R_TURNV_SERVICE_FIN_BANKS	R_TURNV_SERVICE_FIN_INSU
Correlation	28.4	96.7	96.8	93.4
Variable	R_TURNV_SERVICE_PROF	R_TURNV_SERVICE_PUBLIC	R_TURNV_SERVICE_REAL_ESTATE	R_TURNV_SERVICE_TRADE
Correlation	91	33.1	87.3	97.8
Variable	R_VAT_VAL	EXP_COFF_VAL	EXP_COFF_VOL	EXP_MINING_VAL
Correlation	97.7	67.7	17.9	38.5
Variable	EXP_PRINC_CASSITERITE	EXP_PRINC_COFFEE	EXP_PRINC_COLTAN	EXP_PRINC_HIDESANDSKIN
Correlation	-25.7	18	-13.4	-57.6
Variable	EXP_REX_FUEL	EXP_REX_NON_FUEL	EXP_TEA_VAL	EXP_TEA_VOL
Correlation	77.1	93.9	94.1	88.7
Variable	Euro_PMI			
Correlation	30.2			

Table 5: Lag length selection and estimated results for the ARMA benchmark model

ARMA order	Akaike	Schwarz	Hannan-Quinn
0,0	5.893520	5.928124	5.907081
0,1	5.720025	5.823838	5.760710
1,0	* 5.692344	* 5.796157	* 5.733029
1,1	5.722835	5.861253	5.777082

* indicates best model

Table 6: Estimation results of ARMA(1,0)

Dependent Variable: GDP_Y
Method: ARMA Maximum Likelihood (BFGS)
Sample: 2007Q1 2022Q1
Included observations: 61
Convergence achieved after 4 iterations
Coefficient covariance computed using outer product of gradients

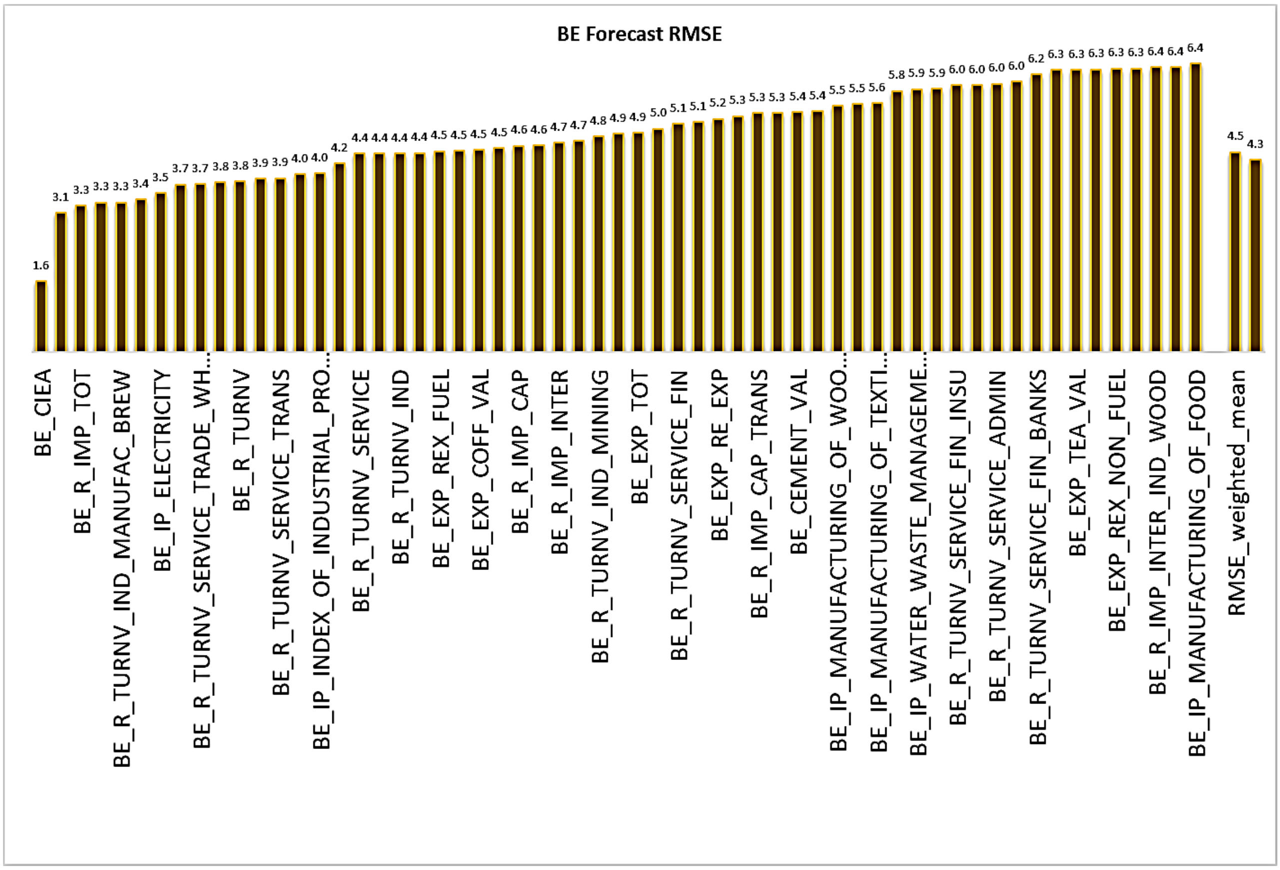
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.184786	1.097048	6.549197	0.0000
AR(1)	0.488333	0.164880	2.961747	0.0044
SIGMASQ	15.66831	1.274495	12.29374	0.0000
R-squared	0.237548	Mean dependent var		7.050914
Adjusted R-squared	0.211256	S.D. dependent var		4.570819
S.E. of regression	4.059401	Akaike info criterion		5.692344
Sum squared resid	955.7668	Schwarz criterion		5.796157
Log likelihood	-170.6165	Hannan-Quinn criter.		5.733029
F-statistic	9.035175	Durbin-Watson stat		1.920439
Prob(F-statistic)	0.000384			
Inverted AR Roots	.49			

Table 7: ARMA test results for agriculture sector model

ARMA order	Akaike	Schwarz	Hannan-Quinn
0,0	12.070	12.103	12.083
0,1	10.870	10.970	10.909
1,0	7.607	7.708	7.647
1,1	* 7.553	* 7.687	* 7.606
* indicates best model			
RMSE			
Naïve model		2.306	
ARMA (1,1)		2.127	

Table 8: Best performing indicators for Non_agriculture GDP nowcast

Bridge Equation	**MIDAS**
CIEA	CIEA
total turnovers of all manufacturing industries	Total imports
Total imports	Petroleum services turnovers
Industrial products intermediate goods imports	Total turnovers
Turnovers of brewery industries	Intermediate goods imports
Turnovers of other manufacturing industries	VAT
Index of industrial production of electricity	Turnovers of brewery industries
Index of industrial production of metal, machinery and equipment	Services sector's turnovers
Turnovers for wholesale and retail trade	Trade services turnovers
Index of industrial production of all manufacturing industries	Real estate turnovers
Total turnovers	Turnovers for wholesale and retail trade
Index of industrial production of chemicals, rubber and plastic	Energy sector turnovers
Transport services turnovers	Other Industrial products intermediate goods imports
VAT	Index of industrial production of chemicals, rubber and plastic
Index of industrial production	index of industrial production
Energy sector turnovers	coffee exports
Services sector total turnovers	Consumer goods imports
Other Industrial products intermediate goods imports	Index of industrial production of furniture and other manufacturing industries
Industry sector total turnovers	total turnovers of all manufacturing industries
Turnovers for hotel and restaurants	Total exports
	Index of industrial production of all manufacturing industries



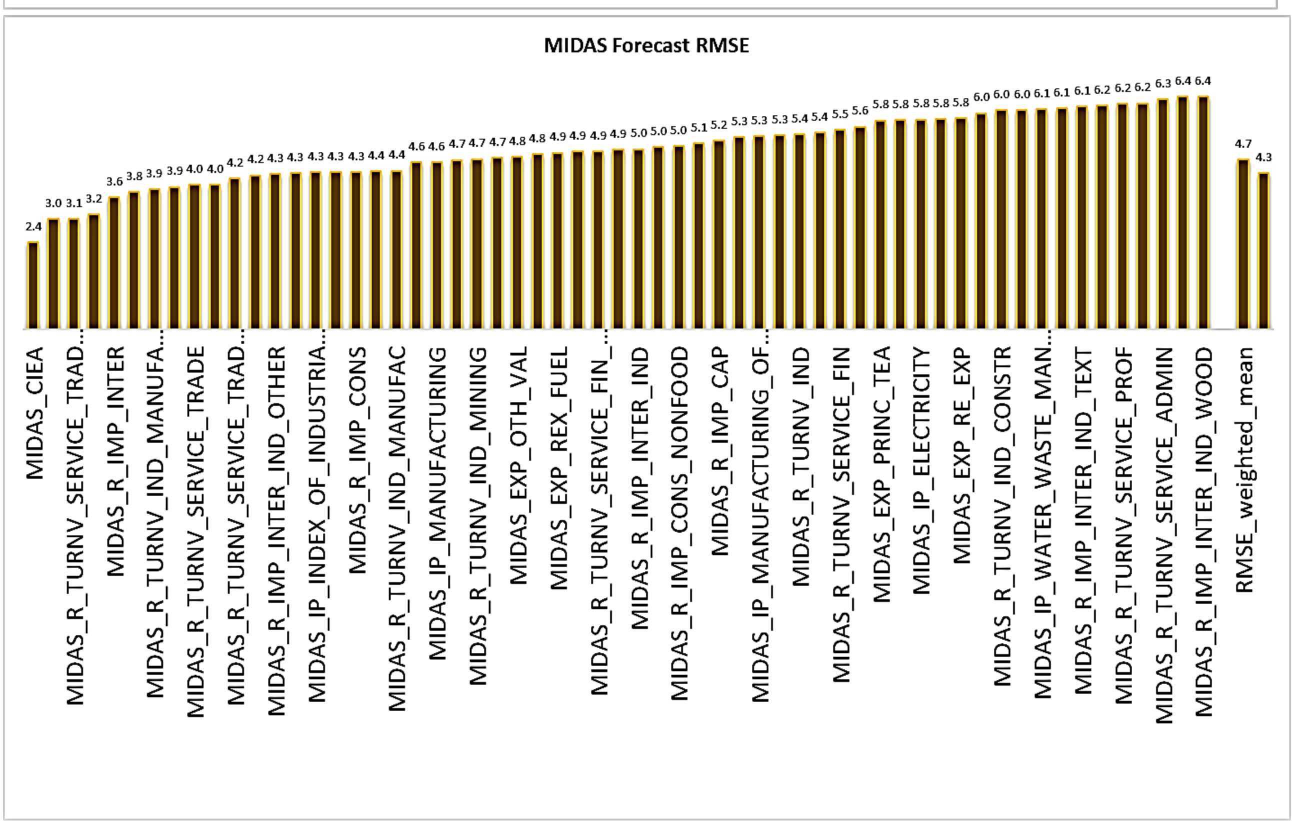


Figure 6: RMSEs ranking of Bridge equations and MIDAS' GDP nowcast