Nowcasting Headline and Sectoral Quarterly GDP

Mohamed Affan Shaneez Latheef

Abstract

Economic data becomes available with significant lags which in turn leads to uncertainty regarding the present state of the economy. In this paper, we set up a framework that can generate nowcasts for headline and sectoral level GDP, and conduct experiments to assess the accuracy of nowcasts. Using a large dataset of 449 economic indicators, we generate nowcasts from a host of univariate and multivariate models, which include traditional econometric nowcasting models and machine learning algorithms. We produce combinations of the best-performing models for each production sector. Furthermore, we explore hierarchical reconciliation methods to ensure that all individual nowcasts would adhere to aggregation constraints and empirically test the nowcast performance of the models and model combinations.

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1 Introduction

Nowcasting refers to the processes used to forecast present or immediate conditions. As it relates to macroeconomics, the need for nowcasting arises primarily because economic data becomes available with significant lags. This is particularly true of GDP data, which is published quarterly and/or annually in most countries. Consequently, policymakers are faced with a significant amount of uncertainty surrounding the immediate present state of the economy.

Even in advanced economies, official GDP data is published with a lag. For instance, in both the USA and the UK, the first release of official quarterly GDP data is published around 1 month after the end of the reference quarter for the data, and in the Euro area the publication lag is around 3 weeks longer (Banbura et al., 2013). The issue of publication lags is even more pronounced in developing and underdeveloped economies. For example, in the Maldives, the Quarterly National Accounts are scheduled for release around 3 months after the end of the reference quarter (Maldives Bureau of Statistics, 2020).

Even though Quarterly GDP data becomes available with significant lags, a lot of economic data series that contain useful information about overall economic activity and productivity are available at higher frequencies. For example, data pertaining to tourist arrivals, industrial output, agricultural output, unemployment, and consumer prices among other series are published monthly in many economies, with a lag of 1-2 months at most. Furthermore, some series such as stock market indices and interest rates are available daily with a lag of 1 day.

It stands to reason that such high frequency data series contains useful information about overall economic activity and can somehow be used to assess the present state of the economy, well ahead of the official release of quarterly GDP data. Therein lies the essence and general premise of nowcasting; which is to utilize data available at higher frequencies to make predictions or nowcasts of an outcome variable that is published at a lower frequency. In the context of our paper, our motivation is to devise a framework within which to use primarily monthly high frequency economic data to make nowcasts of quarterly GDP in the Maldives.

The immediate question that arises then is how best to address the problem of frequency mismatch between a low frequency target variable and higher frequency explanatory variables. Another problem that presents itself, is the fact that publication lags may potentially exist between the set of high frequency explanatory variables as well. For instance, different authorities might have different schedules for publishing data and the data itself may often become available with a lag of around 1 month. For instance, in the Maldives, unofficial tourist arrivals data is available in daily frequency with a lag of around 1 - 2 days and as a result, official monthly data on arrivals becomes available with almost no lag. However, data on tourist bednights comes out with a lag of 1 month. It follows then that at any given point of time, the set of explanatory variables may be unbalanced (i.e. have different number of observations), an issue which is referred to in the nowcasting literature as "jagged edges".

The literature on nowcasting quarterly GDP is quite rich and researchers and practitioners alike have experimented with and refined a number of methodological solutions to these issues. One of the simplest methodological solutions to generate nowcasts from data observed at different frequencies are the so-called bridge equations which deal with the problem of frequency mismatch by simply aggregating the high frequency series to the target frequency (Baffigi et al., 2004; Bulligan et al., 2015; Foroni & Marcellino, 2014; Rünstler et al., 2009; Schumacher, 2016).

Another class of models commonly utilized in the literature are the Mixed Data Sampling (MIDAS) class of models developed by Ghysels et al. (2002) and refined further in subsequent work (Ghysels et al., 2007). The MIDAS class of models can generally be divided into two strands, restricted MIDAS and unrestricted MIDAS. The principal difference between the two being that restricted MIDAS imposes restrictions on the number of parameters to be estimated to overcome the problem of parameter proliferation when large frequency mismatches exist between the outcome and explanatory variables. In economic applications, where the frequency mismatch is often not that large, the unrestricted version of MIDAS is particularly appropriate and indeed has in some studies found to outperform restricted specifications (Foroni & Marcellino, 2014). Andreou et al. (2010), Andreou et al. (2012), and Armesto et al. (2010) provides extensive outlines of the theoretical underpinnings of the restricted MIDAS models. Notable mentions of the applications of the MIDAS class of models to nowcasting GDP include but are not limited to Claudio et al. (2020), Clements & Galvão (2008), Kuzin et al. (2011) and Marcellino & Schumacher (2010).

Another popular class of models used for nowcasting applications are the Dynamic Factor Models (DFMs) proposed by Stock & Watson (2016). Dynamic Factor Modeling is based on the premise that the common dynamics of a large number of data series, can be explained by a few common latent factors, provided that there exists some degree of correlation between the data series (Stock & Watson, 2016). Many empirical studies have established that the latter condition generally holds for macroeconomic data series (Giannone et al., 2005; Stock & Watson, 2012). It is intuitive to grasp how the concept of common factors lends itself to the application of nowcasting quarterly GDP using a set of large high frequency economic data and the nowcasting literature is rife with many applications of DFMs and its variations (Banbura et al., 2013; Bok et al., 2018; Dauphin et al., 2022; Giannone et al., 2008; Giovannelli et al., 2020).

In addition to bridge equations, MIDAS and DFMs, recent research has also begun to incorporate machine learning algorithms and models into nowcasting applications. Richardson et al. (2018) compared the nowcasting performance of several machine learning algorithms such as K-Nearest Neighbours, Lasso, Ridge, Elastic Net, Boosted Trees, Support Vector Regression, Neural Networks and found that they outperformed benchmark statistical models. Claveria et al. (2021) used machine learning based sentiment analyses to nowcast GDP and found that they outperformed traditional time series models. Muchisha et al. (2021) reported that machine learning models outperformed a benchmark AR1 model, and Random Forest models were found to perform best in their application of nowcasting GDP growth in Indonesia. Tiffin (2016) found that Elastic Net and Random Forest models were adept at producing accurate nowcasts of GDP data in Lebanon before the official release. Bolhuis & Rayner (2020) in nowcasting Turkish GDP growth, found that nowcasts generated by combinations of machine learning models, reduced forecast errors by around 30 per cent compared to traditional models.

In the subsequent sections of our paper, we draw from the rich literature on nowcasting GDP to set up a framework which uses a host of traditional econometric and machine learning models, to nowcast Quarterly GDP in the Maldives.

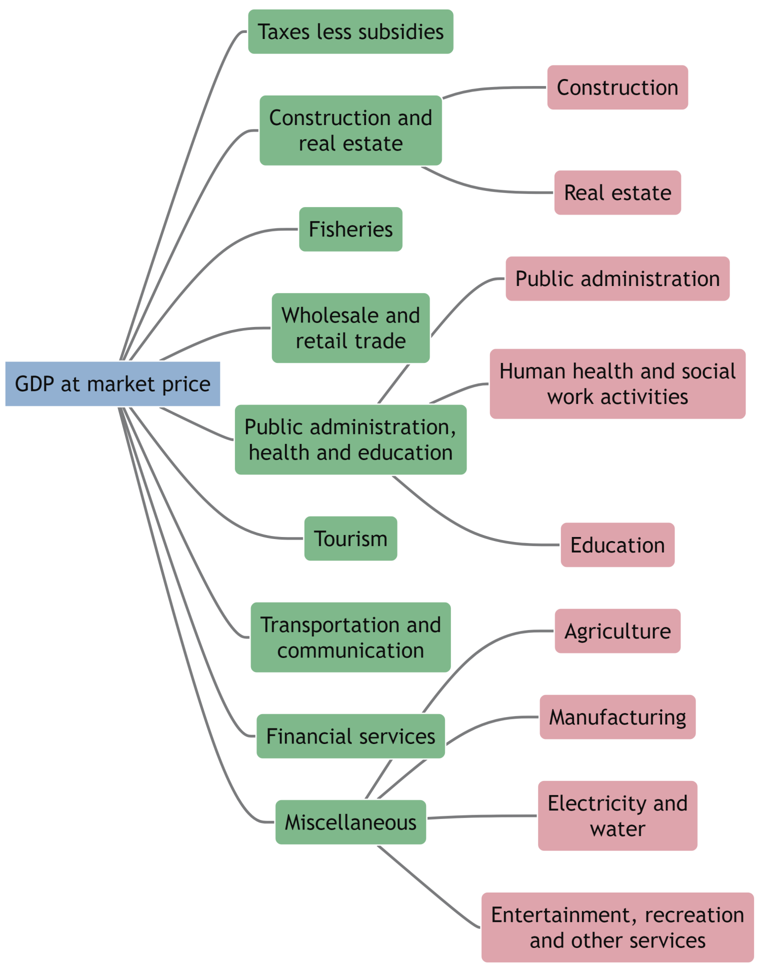
2 Data

We used multiple sources of data to compile the outcome variables, Quarterly National Accounts (QNA) published by Maldives Bureau of Statistics (2024), and the explanatory variables i.e. variables used as predictors in the case of multivariate models. The quarterly national accounts data used in the paper starts from Q1-2003 and ends Q3-2023, amounting to 83 observations, and therefore the explanatory variables were also limited to this time period.

It should be noted that the official QNA release for Q2-2023, which was published by the Maldives Bureau of Statistics (MBS) in November 2023 after rebasing the series from base year 2014 to 2019, only contained data starting from Q1-2014, amounting to 38 data points. In publications of the QNA before it was rebased to 2019, data had been available from Q1-2003. In order to overcome the problems posed by limited number of data points in the new rebased series, the QNA data was extended by producing estimates of the data for the period from Q1-2003 to Q4-2013. The estimates were produced by converting the Annual National Accounts (ANA) (for the period from 2003 to 2013) to quarterly frequency, by benchmarking it to the QNA estimates (with base year 2014) for the corresponding period using Denton Proportional Benchmarking method[1] (Dagum & Cholette, 2006). While the ideal solution would be for MBS to publish official estimates of the rebased back data in forthcoming publications of the QNA, at the time of writing Maldives Bureau of Statistics has indicated that they have no immediate plans to do so.

It should also be noted that the industries in Quarterly National Accounts were aggregated together for computational efficiency based on the importance of industries and how related industries are. As such, the sectors that were nowcasted in this paper were taxes less subsidies, and the industries of fisheries; wholesale and retail trade; tourism, transportation and communication; financial services; construction and real estate; public administration, health and education; and all other industries as miscellaneous. This is illustrated below in Figure 1, where the the sectors we nowcasted are in green and for specific sectors which were aggregated, the sectors in red shows the disaggregated sectors as published in Maldives Bureau of Statistics (2024).

Figure 1: Quarterly National Accounts



[1] The estimates were produced by Mohamed Imthinan Saudulla, Senior Research Analyst at Maldives Monetary Authority.

In the selection of potential independent variables, we attempted to create a dataset similar to the one used in Stock & Watson (2016). The variables can be broadly categorized into activity, trade, fiscal affairs, financial conditions and prices.

Moreover, we also tried to account for the criteria provided by Stock & Watson (1996) as guidelines to follow which specifies that the sample should include the main monthly aggregates and coincident indicators as well as important leading economic indicators, the data should represent broad classes of variables with differing time series properties and the data should have consistent historical definition or when the definitions are inconsistent, it should be possible to adjust the series.

The majority of the data were from domestic sources (including government ministries, state owned enterprises, regulatory bodies and other relevant authorities), and compiled in Maldives Monetary Authority (2024). In addition to domestic data, prices of international commodities including the indices for all commodity prices (PALLFNF); all commodity prices except gold (PEXGALL); food and beverage prices (PFANDB); and industrial inputs prices (PINDU) published in International Monetary Fund (2023) as well as crude oil prices (average of Brent and WTI) published in U.S. Energy Information Administration (2023) were included as candidates for explanatory variables.

This information is summarised in Table 1 and Table 2 below.

Table 1: Data from domestic sources

Number of series	Type
44	Tourism indicators
21	Fisheries indicators
14	CPI series (levels 1 and 2)
79	GFS
78	Monetary
38	External

Table 2: Data from external sources

5 series from external data sources:
EIA Crude oil prices (Average of WTI and Bent)
IMF All commodities index (PALLFNF)
IMF All commodities excluding gold index (PEXGALL)
IMF Food and beverages index (PFANDB)
IMF Industrial inputs index (PINDU)

Furthermore, we constructed an additional 175 variables by aggregation of specific series, and by deflating the nominal variables. The objective of creating the set of deflated series was to remove the price effect as quarterly national accounts are also in real terms, and it is possible that the movements of the deflated series would match those of quarterly national accounts better.

The full list of 449 variables is provided in the Appendix Table 10.

It is important to note that there were steps taken to preprocess, i.e. prepare the data for nowcasting. Firstly, in the case where the full quarter's data is not available (either only the first month or second month of data was available), the issue of jagged edges described above arose. While there are different methods of dealing with this issue, we padded the edges with univariate forecasts to complete the data. In our paper, we used an ARIMA model which was fitted to the data by minimizing the Corrected Akaike Information Criterion (AICc). It should be noted that for fish catch data was forecasted using an ARIMAX model, with fish purchases as the exogenous regressor. More detailed explanations of ARIMA and ARIMAX are available in Section 3.3 and Section 3.1 respectively.

Secondly, it should be noted that the dataset of explanatory variables was unbalanced, with varying starting points for different series. As in the previous case, while there are different methods of dealing with this issue, we have used a K-Nearest Neighbours regression (KNN regression) to impute the missing back data for the series that became available more recently. According to James et al. (2021), the K-Nearest Neighbours regression is a non-parametric method (does not require the correct specification of the underlying probability distribution of the series) that identifies the “K” training observations that are most closely related to the prediction point, and estimates using the average of all the training responses. This can be mathematically expressed as

$$\hat{f}(x_0) = \frac{1}{K} \sum_{x_i \in \mathcal{N}_0} y_i,$$

where x_0 is a prediction point, and the identified training observations that are similar to x_0 are represented by $\mathcal{N}_0$ (James et al., 2021).

Furthermore, additional preprocessing was also carried out as required for specific models. An important point of reference for this step was the guidelines provided in Kuhn & Silge (2022).

3 Methodology

In order to generate the nowcasts from the preprocessed data, we have used an expansive methodology which incorporates a multitude of different classes of models, and combinations of these models. These include traditional econometric nowcasting models such as Bridge equations, MIDAS (Mixed Data Sampling) models, Dynamic Factor models (DFMs) and machine learning algorithms including Lasso, Ridge, Elastic Net, Random Forest, Support Vector regression, XGBoost and LightGBM.

We have further produced combinations of the nowcasts generated by models, based on the best-performing models for each target sector. Lastly, we have also specified best fitting ARIMA and ETS models to generate nowcasts as well. A simple AR(1) model was specified as the benchmark model against which we evaluate the nowcast performance of the other models. The following subsections outline the theoretical underpinnings of the main classes of models that we have used in this paper, the methodology used for reconciling the nowcasts of headline Quarterly Real GDP with the nowcasts of the economic sectors, and for producing combinations of the nowcasts.

3.1 Bridge

Bridge models are one of the simplest techniques used to model mixed frequency data and have been used extensively in the literature on nowcasting quarterly GDP using monthly, weekly or daily explanatory variables (Baffigi et al., 2004; Bulligan et al., 2015; Foroni & Marcellino, 2014; Rünstler et al., 2009; Schumacher, 2016). The premise behind bridge models is very simple and involves the time aggregation of a set of higher frequency explanatory variables to the same frequency as the lower frequency predicted variable.

The method used for time aggregation depends primarily on the stock/flow nature of the high frequency variable. Stock variables are averaged, while flow variables are summed up to aggregate the high frequency observations to the desired lower frequency (Schumacher, 2016).

Thus, closely following Bulligan et al. (2015) and Schumacher (2016) the bridge model where the target variable is observed at quarterly frequency can be generalized as follows:

$$Y_{t_q} = \beta_0 + \sum_{i=1}^{j} \beta_i(L) x_{it_q} + \epsilon_{t_q}$$

where y_{t_q} is the high frequency target variable observed at frequency q. The target variable is modelled on a constant β_0 and up to j explanatory variables x_{t_m}, which are observed at the higher monthly frequency as denoted by the m. The high frequency variables once aggregated to the target frequency by averaging or summation, is denoted as x_{it_q}.

The parameters β_i, … , β_j are then usually estimated via OLS in the literature. In addition to this, we also specify a second specification of the same bridge models with (Seasonal) ARIMA errors or (S)ARIMAX, where ϵ_{t_q} is modelled as a SARIMA (p,d,q)(P,D,Q)(4) process and the parameters are estimated via Maximum Likelihood Estimation. We further specify, each of the models estimated via OLS and MLE, in both the level and y-o-y growth of the variables, yielding the following 4 variations of the bridge equations.

1. Bridge in levels estimated via OLS
2. Bridge in growth estimated via OLS
3. Bridge in levels with ARIMA errors estimated via MLE
4. Bridge in growth with ARIMA errors estimated via MLE

We have used the same explanatory variables for the all variants of the bridge and MIDAS models. The explanatory variables were selected primarily using judgement on the most appropriate indicators available for the respective sectors of Real GDP. It should be noted that our judgement was informed by the actual indicators that the Maldives Bureau of Statistics uses in the compilation of National Accounts statistics (Maldives Bureau of Statistics, 2020). The list of explanatory variables used in the bridge and MIDAS models are outlined in Table 3.

Table 3: Explanatory variables used in Bridge and MIDAS equations

Dependent variable	Explanatory variable
GDP at market price	Bednights from resorts
Taxes less subsidies	Bednights from resorts

Dependent variable	Explanatory variable
Fisheries	Fish catch (forecasted using fish purchase data)
Wholesale and retail trade	Total imports, deflated by CPI
Tourism	Bednights from resorts
Transportation and communication	Arrivals
Financial services	Average loans, and average deposits
Construction and real estate	Construction related imports, deflated by PINDU
Public administration, health and education	Salaries and allowances, deflated by CPI
Miscellaneous	Bednights from resorts

3.2 MIDAS

The MIDAS (Mixed Data Sampling) regression framework introduced by Ghysels et al. (2002) facilitates the estimation of regressions in which the variables are sampled at different frequencies. While the bridge models can also - to a certain extent - address the problem of frequency mismatch via time aggregation, it suffers from the obvious drawback of being unable to fully capture the dynamic relationships between a low frequency target variable and a set of high frequency variables and their lags. For example, when considering the case of nowcasting quarterly GDP using a monthly set of indicators, valuable information on the different relationships between the target variable and within quarter months and their lags, cannot be fully captured when simply time-aggregating the monthly series to quarterly. The MIDAS framework overcomes this problem by offering a flexible and tractable framework that can handle frequency mismatches both between dependent and explanatory variables and within the set of explanatory variables.

The MIDAS class of models are broadly categorized into unrestricted (U-MIDAS) and restricted (R-MIDAS). U-MIDAS models can be estimated via OLS, impose no restrictions on the parameters to be estimated, and are appropriate when the frequency mismatch between the variables is not very large. This is often the case in macroeconomic applications such as nowcasting GDP, where the low frequency variable is observed quarterly and the high frequency variables in monthly frequency.

However, when the frequency mismatch is large (for example quarterly and daily), the number of parameters to be estimated increases substantially, resulting in the problem of parameter proliferation. Restricted MIDAS regressions address this problem by imposing restrictions on the number of parameters to be estimated via non-linear least squares (NLS) using functional lag polynomials. Given the above, the R-MIDAS model as proposed by Ghysels et al. (2002), generalized to the case of nowcasting quarterly GDP using monthly data, can be represented as follows

$$Y_{t_q} = \beta_o + \sum_{i=1}^{p} \beta_i L^i Y_{t_q} + \gamma \sum_{k=1}^{j} \Phi(k;\theta) L_m^k X_t + \epsilon_t$$

Where Y_{t_q} represents the low frequency target variable observed at quarterly frequency, which is modelled on a constant β_0, up to p lags of the target variable denoted by the lag operator L^i, and a set of high frequency variables X_t and up to j lags. The function $\phi(k;\theta)$ is a polynomial that determines the weights for temporal aggregation and can have a number of functional forms such as the beta formulation used by Ghysels et al. (2002) or the exponential Almon lag specification used by Ghysels et al. (2007) which is outlined below

$$\phi(k;\theta_1,\theta_2) = \frac{exp(\theta_1 k + \theta_2 k^2)}{\sum_{j=1}^{M} exp(\theta_1 j + \theta_2 j^2)}$$

The hyperparameters θ_1 and θ_2 dictate the shape of the weighting function. In this paper we have used only the exponential Almon lag polynomial function in our R-MIDAS models. In order to estimate the MIDAS models, we have utilized the R package `midasr` developed by Ghysels et al. (2016). The full list of explanatory variables used in the MIDAS equations are outlined in Table 3.

3.3 ARIMA

ARIMA is an acronym for (Auto Regressive Integrated Moving Average) and is one of the most widely utilized univariate time-series modelling and forecasting techniques. As the name implies, the ARIMA model is comprised of three main components; namely the autoregressive (AR) component which captures the relationship between a variable and its past observations; the integration (I) component which specifies the degree to which the series is differenced to achieve stationarity; and finally the moving average (MA) component which captures the relationship between the variable and its historic error terms in a specified model (Hyndman & Athanasopoulos, 2021).

Following Hyndman & Athanasopoulos (2021) the ARIMA model with p autoregressive terms, d degrees of differencing, and q moving average terms or the $ARIMA(p,d,q)$ with a constant can be generally written as:

$$y_t = \beta_o + \phi_1 y_{t-1} + ... + \phi_p y_{t-p} + \theta_1 \epsilon_{t-1} + ... + \theta_q \epsilon_{t-q} + \epsilon_t$$

Written in backshift notation using the backshift operator B, the above model can be rewritten as:

$$(1 - \phi_1 B - ... - \phi_p B^p)(1-B)^d y_t = \beta_o + (1 + \theta_1 B + ...\theta_q B^q)\epsilon_t$$

The general case above can be extended to control for the effects of seasonality and the Seasonal ARIMA model is generally reported as $ARIMA(p,d,q)(P,D,Q)m$, where the uppercase notation represents the orders of the autoregressive, differencing and moving average terms for the seasonal component of the model, and the m represents the seasonal period or the number of observations per year (i.e m=4 for quarterly data and m=12 for monthly data). The general SARIMA model (with no constant) can also be expressed using back shift notation as follows

$$\begin{aligned}&(1 - \phi_1 B - ... - \phi_p B^p)(1 - \Phi_1 B^m - ... - \Phi_P B^{Pm})(1-B)^d(1-B^n)^D y_t = \\ &(1 + \theta_1 B + ... + \theta_q B^q)(1 + \Theta_1 B^m + ... + \Theta_Q B^{Qm})\epsilon_t\end{aligned}$$

In the econometric forecasting literature, it is common practice to utilize simple ARIMA models as benchmark models to gauge the forecast performance of other models. In our nowcasting application, we have utilized a simple first-order autoregressive model or $ARIMA(1,0,0)(0,0,0)4$. Additionally the best-fitting ARIMA models have also been used to generate nowcasts. The "best-fitting" ARIMA models are the models with the permutation of (p,d,q) and (P,D,Q) orders that minimizes the Corrected Akaike Information Criterion, AIC_c (Akaike Information Criterion corrected for small sample bias).

Hyndman & Athanasopoulos (2021) notes that for an $ARIMA(p,d,q)$ model, the AIC is usually written as

$$AIC = -2log(L) + 2(p+q+k+1)$$

where L represents the likelihood of the data, and, $k = 1 if c \neq 0$ and $k = 0 if c = 0$.

Considering the above, the Corrected AIC is written as

$$AIC_C = AIC + \frac{2(p+q+k+1)(p+q+k+2)}{T-p-q-k-2}$$

3.4 ETS

The ETS (Error, Trend, Seasonality) model is a univariate time-series model that is based on the concept of exponential smoothing. ETS models are a more refined version of the Simple Exponential Smoothing models, that produce forecasts by assigning decaying weights to past observations of itself. While SES models are appropriate for modeling data series with no discernible trend or seasonal patterns, the ETS can be considered an extension of SES that can handle trends and seasonality in the data (Hyndman & Athanasopoulos, 2021).

As the name implies, ETS models time series by decomposing it into three main components: Error, Trend, and Seasonality. The error component captures the stochastic volatility in a time-series, while the trend component captures the general direction or movement of the series, and the seasonality component captures time patterns in the data (Hyndman & Athanasopoulos, 2021).

The trend component can take the form additive, denoted by A , whereby the historically observed trend is assumed to carry on indefinitely into the future, or additive damped denoted as A_d , whereby the trend is "dampened" by a smoothing parameter. Additionally, seasonal component can be either additive or multiplicative processes, denoted as A and M respectively. The case where neither process is present is denoted by N. Lastly, the each of the models with the above permutations can either have additive or multiplicative errors, denoted respectively by A or M

Thus, the ETS model can be specified as $ETS(.,.,.)$ with the following possibilities for for each of the three components, $E = [A, M]$, $T = [N, A, A_d]$ and $S = [N, A, M]$. For a given time-series, the best-fitting specification is the combination that minimizes the AIC_c whereby

$$AIC = -2log(L) + 2k$$

$$AIC_c = AIC + \frac{2k(k+1)}{T-k-1}$$

where L is the likelihood of the model and k represents the number of parameters and initial states, and T the number of observations in the sample (Hyndman & Athanasopoulos, 2021).

3.5 Neural Network Autoregression (NNAR)

Neural Network Autoregressions are an advanced class of models that combine traditional autoregressive (AR) modelling with the architectural framework of Neural Networks. Neural Networks models are organized in layers and take input from the bottom layers to produce a forecast in the top output layer. The simplest Neural Networks are easy to conceptualize, as they contain no intermediate hidden layers, and take inputs from n number of predictors in a single layer to produce an output or a forecast. This simplest form of Neural Networks can be thought of as a counterpart to a linear regression with n explanatory variables.

The neural network counterpart to the $n * 1$ coefficients attached to the predictors in a linear regression, are called weights on the predictors, which are selected through a learning algorithm that seeks to minimize a traditional loss function such as MSE or RMSE. The neural network becomes non-linear, when hidden intermediate layers, are included in the network. In practice, the number of hidden layer and number of nodes in each layer are specified by the researcher, and are usually selected through cross-validation (Hyndman & Athanasopoulos, 2021).

In a Neural Network Autoregression, the lags of a time series can be used as predictors or inputs to the network. We follow the notation used in Hyndman & Athanasopoulos (2021) to specify the Neural Network Model as $NNAR(p, k)$, where p determine the number of lags used as inputs for the network, and k denotes the number of nodes in the hidden layer. Thus it follows that a $NNAR(p, k)$ model is neural network where $\sum_{i=1}^{p} Y_{t-i}$ lags are used as inputs to forecast Yt, in a network that contains a hidden layer with k nodes.

The NNAR can also handle seasonality by including seasonal autoregressive terms. Closely following the standard notation for reporting SARIMA models, an $NNAR(p, P, k)m$ model takes p lags and P seasonal lags as inputs in the network with k nodes in the hidden layer (Hyndman & Athanasopoulos, 2021).

3.6 Temporal Hierarchical Forecasting (Thief)

Temporal Hierarchical Forecasting (Thief) models introduced by Athanasopoulos et al. (2017) is based on the idea of producing reconciling independent forecasts of the different temporal hierarchies of a time series. For a time-series observed at a given frequency m, it is possible to construct several non-overlapping aggregate series at different frequencies up to the annual frequency. Athanasopoulos et al. (2017) defines temporal hierarchies as "the structural connection across the levels of aggregation." It is notable that the Thief framework is model-independent, and can incorporate any time-series models such as ARIMA and ETS

For a time-series observed at monthly frequency, it is possible to create aggregated series at quarterly and annual frequency. Indeed, it is also possible to create even more uncommon aggregations of 2-month, 4-month or 6-month series. In theory, for a monthly series, any k aggregate series can be constructed provided that k is a factor of 12, and has a seasonal period, $12/k$.

More generally for a time series y_t observed at frequency m, the k aggregate series can be mathematically written as

$$y_j^{[k]} = \sum_{t=t^*+(j-1)k}^{t^*+jk-1} y_t$$

where $j = 1, \dots, [T/k]$ and $M_k = m/k$ is the seasonal period

3.7 Ridge regression, Lasso and Elastic Net

Ridge regression, lasso (Least Absolute Shrinkage and Selection Operator) and elastic net are modified linear regression methods that introduce different types of penalties that are imposed on the use of coefficients to enhance prediction accuracy (commonly referred to as regularization) (Dauphin et al., 2022). Constraining or regularizing the coefficient estimates, or equivalently, shrinking the coefficient estimates towards zero has the benefit that it can significantly reduce their variance (James et al., 2021).

James et al. (2021) explained that the ordinary least squares (OLS) fitting procedure estimates the parameters ($\beta_0, \beta_1, \dots, \beta_p$) using the value that minimizes the residual sum of squares (RSS) as shown below;

$$RSS = \sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij})^2.$$

While ridge regression is very similar to OLS, it estimates the ridge regression coefficient estimates $(\hat{\beta}^R)$ by minimizing a slightly different quantity,

$$\begin{aligned}
&\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij})^2 + \lambda \sum_{j=1}^{p} \beta_j^2 \\
&= RSS + \lambda \sum_{j=1}^{p} \beta_j^2,
\end{aligned}$$

where $\lambda \geq 0$ is tuning parameter to be determined separately. Similarly to the OLS, ridge regression seeks coefficient estimates that fit the data well by minimizing the RSS, but adds a second term, the shrinkage penalty, $(\lambda \sum_j \beta_j^2)$, which shrinks the estimates of β_j (James et al., 2021). The authors (2021) explained further that the tuning parameter λ controls the relative impact of these two terms on the coefficient estimates, whereby $\lambda = 0$ would produce OLS estimates and as $\lambda \to \infty$, the impact of the shrinkage penalty grows and the ridge regression coefficient estimates will approach zero. However, it should be noted that while increasing the λ will tend to reduce the magnitudes of the coefficients, it will not result in exclusion of any of the variables (unless $\lambda = \infty$).

According to James et al. (2021), the lasso is a more recent alternative to the ridge regression that overcomes this by changing the objective function slightly whereby the lasso coefficients $(\hat{\beta}^L)$ minimize the quantity

$$
\begin{aligned}
&\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij})^2 + \lambda\sum_{j=1}^{p}|\beta_j| \\
&= RSS + \lambda\sum_{j=1}^{p}|\beta_j|.
\end{aligned}
$$

As with the ridge regression, the lasso shrinks the coefficient estimates towards zero, but it has the effect of forcing some of the coefficient estimates to be exactly equal to zero when the tuning parameter λ is sufficiently large (James et al., 2021). The authors (2021) noted that although it leads to models that are more interpretable, it does not necessarily improve prediction accuracy.

Finally, elastic net introduced the elastic net penalty whereby the objective function is specified as

$$
\begin{aligned}
&\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij})^2 + \lambda\sum_{j=1}^{p}(\alpha\beta_j^2 + (1-\alpha)|\beta_j|) \\
&= RSS + \lambda\sum_{j=1}^{p}(\alpha\beta_j^2 + (1-\alpha)|\beta_j|),
\end{aligned}
$$

which allows the model to select variables like the lasso and shrink the coefficients of correlated predictors like ridge, and the parameter term α determines the mix of the penalties (Hastie et al., 2009).

3.8 Support Vector Regression

Support vector regressions seek coefficient estimates that minimizes loss differently, where only residuals larger in absolute value than some positive constant (ϵ) contribute to the loss function (James et al., 2021).

According to Hastie et al. (2009), to estimate the regression coefficients, the support vector regression minimizes the objective function,

$$
\begin{aligned}
H(\beta, \beta_0) &= \sum_{i=1}^{N} V(y_i - f(x_i)) + \frac{\lambda}{2}||\beta||^2, \\
f(x) &= x^T\beta + \beta_0,
\end{aligned}
$$

where

$$
V_\epsilon(r) = \begin{cases} 0 & \text{if } |r| < \epsilon, \\ |r| - \epsilon & \text{otherwise.} \end{cases}
$$

This illustrates the "ϵ-insensitive" error measure as it ignores residuals or errors that are greater than ϵ (Hastie et al., 2009). The authors (2009) further explained that this has the benefit of making the fitting less sensitive to outliers in addition to flattening the contributions of the cases with small residuals.

Additionally, it should be noted that while ϵ is a parameter of the loss function V_ϵ, the quantity λ is a more traditional regularization parameter as seen above (Hastie et al., 2009).

According to Kuhn & Johnson (2013), the support vector regression can be extended to adapt to nonlinear relationships, by using different types of kernel functions to generalize the regression model and encompass nonlinear functions of the predictors.

Dauphin et al. (2022) explained that while support vector regressions can overcome the drawbacks of linear regression models including linearity, collinearity, overfitting, and high dimension issues, the performance depends on the proper selection of the kernel function and regularization parameters. However, the authors (2022) further noted that complicated kernel functions or parameters may limit the model's interpretability.

3.9 Random Forests

According to (James et al., 2021), bootstrapping is the process of taking repeated samples from a single training data set and generating different training data sets. Random forests build a number of decision trees on such bootstrapped training samples and averages all the predictions (James et al., 2021). However, in the process of building the decision trees, a random sample of predictors is chosen as candidates at each split in the tree (James et al., 2021).

The authors (2021) further explained that this process ensures that the different bootstrapped decision trees are not highly correlated, as it forces each split to consider only a subset of predictors – a process that can be considered as decorrelating the trees, and hence the average of the resulting trees are less variable and more reliable.

The main tuning parameters of the model include the number of randomly selected predictors to choose from at each split and the number of decision trees to be trained (Kuhn & Johnson, 2013).

3.10 Gradient Boosting

Boosting is a general approach that can be applied to many statistical learning methods for regression or classification (James et al., 2021). While originally, boosting models were developed for classification problems and later extended to the regression setting, Friedman's stochastic gradient boosting machine had become widely accepted as the boosting algorithm of choice (Kuhn & Johnson, 2013).

According to James et al. (2021), gradient boosting grows decision trees sequentially, with each tree using information from previously grown trees. However, instead of bootstrap sampling, it fits a tree on a modified version of the original data set (James et al., 2021).

Gradient boosting has three main tuning parameters – the number of trees which determines whether the model overfits, the shrinkage parameter λ which controls the rate at which the boosting learns, and the number of splits in each tree which controls the complexity of the boosted ensemble or the interaction depth of the model (James et al., 2021).

It should be noted that while constraining the learning process with a small λ is important to avoid overfitting, a very small λ can require training a large number of trees in order to achieve good performance, and therefore the value of the shrinkage parameter is inversely proportional to the computation time required to find an optimal model (James et al., 2021; Kuhn & Johnson, 2013).

The algorithms that we used for gradient boosting are XGBoost (eXtreme Gradient Boosting) and LightGBM (Light Gradient Boosting Machine).

3.11 Dynamic Factor Models

According to Stock & Watson (2016), dynamic factor models (DFMs) is based on the general idea that the common dynamics of a large number of time series variables stem from a relatively small number of unobserved or latent factors that evolve over time. Banbura et al. (2013) explained that if there is a high degree of co-movement amongst the series, the bulk of the dynamics can be captured by a few factors. The author (2013) further showed that there is considerable empirical evidence for this in the case of large panels of macroeconomic variables.

In dynamic factor models, each series is modelled as the sum of two orthogonal or independent components – a common component driven by a handful of unobserved factors which captures the joint dynamics, and idiosyncratic residuals which captures any remaining individual movement (Banbura et al., 2013; Stock & Watson, 2016).

According to Banbura et al. (2013), the most common version of dynamic factor models, in the context of nowcasting, specifies that the high frequency variables, Y_t , have a factor structure and that the factors, F_t, follow a vector autoregressive (VAR) process as shown below.

$$\begin{aligned} Y_t &= \mu + \Lambda F_t + E_t \qquad E_t \, i.i.d. N(0, \Sigma_E) \\ F_t &= \Phi(L) F_t + U_t \qquad U_t \, i.i.d. N(0, \Sigma_U) \end{aligned}$$

Banbura et al. (2013) further explained that following estimates of the factors, nowcasts are obtained via a regression of GDP on temporally aggregated factor estimates, which can be mathematically expressed as:

$$y_{t,1}^{k_1} = \alpha + \beta F_{t,\Omega_v}^{k_1} + e_t^{k1}, \;\; t = k_1, 2k_1, \dots .$$

In this paper, in order to test and see which whether subsets of variables improved on the performance of the model, we have run dynamic factor models with four different variations of the full data set;

1. Using both nominal and real variables
2. Using only nominal variables
3. Using only real variables
4. Providing the important variables selected by lasso

3.12 Model Stacking

According to Kuhn & Silge (2022), model stacking is a method of creating a model ensemble, where the predictions of multiple single learners or models are aggregated to make one prediction and produce a high-performance final model. The candidates to be included in the stack can include different types of models as well as different configurations of the same model (Kuhn & Silge, 2022).

In order to assess the candidate models for a model stack, a meta-learning model is created from the training set predictions and the corresponding observed outcome data (Kuhn & Silge, 2022). The authors (2022) further explained that while any model can be used for meta-learning, the most commonly used model is a regularized general linear model – specifically one regularized via the lasso penalty. Advantages of using a lasso include the ability to remove candidates or model types from the ensemble, and the alleviation of the correlation between the candidate models (Kuhn & Silge, 2022).

In this paper, all models that were supported by the `R` package `tidymodels` and had no computational issues were provided as candidates for the model stack – which would include all models except bridge, MIDAS, DFMs, and the univariate models. Additionally, Support Vector Regression and LightGBM were also excluded due to issues that arose in the stacking process when they were included, whereby the weights given to these models and the resulting forecasts were not sensible or resulted in numeric instabilities.

It should be noted that while it is possible to use ridge and elastic net as meta-learning models for the process of model stacking as well, we only used lasso due to the increased computational burden and the similarities in the model performance based on preliminary experiments.

3.13 Reconciliation

In the paper, we have nowcasted both GDP and the production side sectors which leads to a need to produce coherent forecasts, i.e. forecasts that adhere to aggregation constraints. Additionally, it is logical to assume different methods may perform better for different sectors as the time series have different features in them, which resulted in a need to be able to possibly combine forecasts from different models for different sectors. Therefore, an important step to tie all the forecasts together is forecast reconciliation. In addition to being able to produce coherent forecasts, Athanasopoulos et al. (2020) has demonstrated that in many empirical settings, forecast reconciliation methods improve forecast accuracy as well.

The details for the reconciliation methods used in this paper are provided in the following subsections.

3.13.1 Bottom-up

According to Athanasopoulos et al. (2020), in the bottom-up approach, forecasts for the most disaggregate level are aggregated to obtain forecasts for other series in the hierarchy. A set of coherent forecasts for the whole hierarchy using the bottom-up approach is given by;

$$\tilde{y}^{BU}_{T+h|T} = S\hat{b}_{T+h|T},$$

where $\hat{b}_{T+h|T}$ refers to the bottom-level forecasts and S refers to the summing matrix which reflects the linear aggregations constraints and in particular, how the bottom-level series aggregate to levels above (Athanasopoulos et al., 2020).

An important point to consider is that while bottom-up forecasts has the advantage of no information being lost due to aggregation, bottom-level data can potentially be highly volatile or very noisy which could make it more challenging to forecast (Athanasopoulos et al., 2020).

3.13.2 Optimal Minimum Trace (MinT) Reconciliation

According to Athanasopoulos et al. (2020), single-level approaches such as bottom-up approach uses information from a single level of aggregation and ignores any correlations across levels of a hierarchy, which leads us to MinT reconciliation. In MinT reconciliation, forecasts for all series across all levels of hierarchy are produced (referred to as base forecasts), before the base forecasts are adjusted to produce coherent forecasts and it incorporates the full correlation structure of the hierarchy (Athanasopoulos et al., 2020).

This is mathematically expressed as;

$$\tilde{y}_{T+h|T} = SG\hat{y}_{T+h|T},$$
$$G = (S'W_h^{-1}S)^{-1}S'W_h^{-1},$$

where G is a matrix that produces and adjusts the forecasts for reconciliation (Athanasopoulos et al., 2020). The authors (2020) noted that a crucial challenge is estimating W_h and there are different possible alternative estimators for it. Following subsections detail the two main methods that we have used in the paper.

3.13.2.1 Weighted Least Squares (WLS)

The weighted least squares (WLS) estimator sets $W_h = k_h\text{diag}(\hat{W}_1)$ for all $h(k_h > 0)$, where

$$\hat{W}_1 = \frac{1}{T}\sum_{t=1}^{T}\hat{e}_t\hat{e}_t'$$

is the unbiased sample estimator of the in-sample one-step-ahead base forecast errors (Athanasopoulos et al., 2020). The estimator scales the base forecasts using the variance of the in-sample residuals, and hence is described and referred to as the weighted least squares estimator applying variance scaling (Athanasopoulos et al., 2020).

3.13.2.2 MinT (Shrink)

Athanasopoulos et al. (2020) explained that the MinT (Shrink) estimator sets $W_h = k_h\hat{W}_1^D$ for all $h(k_h > 0)$, where $\hat{W}_1^D = \lambda_D\text{diag}(\hat{W}_1) + (1-\lambda_D)\hat{W}_1$ is a shrinkage estimator with diagonal target and shrinkage intensity parameter

$$\hat{\lambda}_D = \frac{\sum_{i\neq j}\hat{Var}(\hat{r}_{ij})}{\sum_{i\neq j}\hat{r}_{ij}^2},$$

where $\hat{r}_{ij}$ refers to the (i, j) element of $\hat{R}_1$, the one-step-ahead sample correlation matrix. Therefore, the off-diagonal elements of $\hat{W}_1$ are shrunk towards zero while the diagonal elements (variances) remain unchanged (Athanasopoulos et al., 2020).

3.13.3 Combinations

In this section, we will detail how we selected the best models for each sector and used forecast reconciliation methods to combine different models into a coherent forecast. As such, the two main criteria that we have used are;

1. Whether we should take only the months with full quarterly data available or all months, some of which would have partial quarterly data with ARIMA forecasts used to pad the remaining months in the quarter.
2. When selecting the best model, whether we should check the entire experiment or whether we should only look at the past 12 months. As a side effect, when the entire experiment is checked, the combination remains static throughout the experiment, while when only the past 12 months are taken, the combination is dynamic with different models being selected based on its recent performance.

This allowed us to create four combinations as illustrated below;

Table 4: Combinations created using forecast reconciliation methods.

	Dynamic	Static
Padded with forecasts	Combination 1	Combination 3
Not padded with forecasts	Combination 2	Combination 4

4 Experiment

In order to assess the best models for nowcasting, an expanding widow experiment was run from January 2019 to September 2023, with 57 windows. The first window which started from January 2019 used all data until then and therefore has 192 monthly data points, while the last window which started from September 2023 has 248 monthly data points.

Importantly, the experiment was conducted on a monthly frequency which allows us to see how the models perform when full data for a quarter is available as opposed to when the variables are padded with forecasts to complete the quarter.

The main measures used to assess the models was Root Mean Squared Error (RMSE). The following is a mathematical representation of the measure as shown in Hyndman & Athanasopoulos (2021);

$$\text{RMSE} = \sqrt{\text{mean}(e_t^2)},$$
$$\text{where } e_{T+h} = y_{T+h} - \hat{y}_{T+h}.$$

The models were also assessed based on their performance in nowcasting only the headline quarterly GDP, only the sector level series and all series combined. This enabled us to be able to look for differences in performance and look deeper into why a model may perform better or worse.

In addition to evaluating the performance of the nowcasts using RMSE, the nowcasts generated from all models werel also compared with the nowcasts obtained from a benchmark AR1 model, at a forecast horizon of one quarter ahead. This allowed us to gauge the performance gains of each model compared to the benchmark model. The "Percentage change" column in Table 5, Table 6 , and Table 7 shows the improvement in RMSE for each respective model compared to the RMSE of the benchmark model. A negative figure represents an improvement over the benchmark model (i.e lower RMSE of the respective model compared to the benchmark model).

5 Results

In the experiment, we had tested 112 models, from which 25 are the base models (variations of model classes without any forecast reconciliation applied). With three types of reconciliation applied to the models and 4 combinations created, a total of 87 reconciled models were tested. In this section, only the reconciled models were considered as we require coherent nowcasts i.e. nowcasts that adhere to the aggregation constraints.

When examining the results, we initially checked the error measure of RMSE for all series, with both the months that were padded with forecasts as well as quarters with full data as shown in Table 5 below.

Table 5: Top 10 models for all series based on RMSE for the forecast horizon of one quarter ahead. Percentage change shows the change in RMSE when compared to the benchmark model, AR1.

Model	RMSE	Percentage change
Combination_3 Rec_BU	283,495,618	-79.57
Bridge_ARIMA_levels Rec_BU	285,392,102	-79.44
Bridge_ARIMA_levels Rec_MinT	288,003,877	-79.25
Combination_3 Rec_MinT	288,355,283	-79.22
Combination_4 Rec_BU	289,294,066	-79.16
Bridge_ARIMA_levels Rec_WLS	296,245,751	-78.66
Combination_3 Rec_WLS	301,402,949	-78.28
Combination_4 Rec_WLS	316,497,208	-77.20
Combination_4 Rec_MinT	316,563,543	-77.19
Bridge_levels Rec_MinT	556,356,860	-59.92

In terms of model classes, it can be seen that the best-performing models are the reconciled forecast combinations and the bridge equations with ARIMA errors. Specifically, the three best-performing models are Combination 3 reconciled using bottom-up approach (Combination_3 Rec_BU), Bridge ARIMA levels reconciled using bottom-up approach (Bridge_ARIMA_levels Rec_BU) and Bridge ARIMA levels reconciled using MinT (Shrink) (Bridge_ARIMA_levels Rec_MinT). The best model performed significantly better over the benchmark model, showing approximately 80% lower RMSE for all series. We had similar findings when examining just the top level quarterly GDP series, and just the sectors of GDP as shown in Table 6 and Table 7 respectively. The RMSE's for the full list of models can be found in Table 11, Table 12, and Table 13 in the Appendix.

Table 6: Top 10 models for headline quarterly GDP based on RMSE for the forecast horizon of one quarter ahead. Percentage change shows the change in RMSE when compared to the benchmark model, AR1.

Model	RMSE	Percentage change
Combination_3 Rec_BU	703,713,467	-82.05
Bridge_ARIMA_levels Rec_BU	708,575,299	-81.93
Bridge_ARIMA_levels Rec_MinT	716,982,850	-81.71
Combination_3 Rec_MinT	723,244,818	-81.55
Combination_4 Rec_BU	725,165,517	-81.50
Bridge_ARIMA_levels Rec_WLS	742,868,195	-81.05
Combination_3 Rec_WLS	768,135,973	-80.41
Combination_4 Rec_MinT	794,464,741	-79.73
Combination_4 Rec_WLS	801,784,575	-79.55
Bridge_levels Rec_MinT	1,408,459,288	-64.07

Table 7: Top 10 models for the sectors of GDP (bottom level series) based on RMSE for the forecast horizon of one quarter ahead. Percentage change shows the change in RMSE when compared to the benchmark model, AR1.

Model	RMSE	Percentage change
Combination_3 Rec_MinT	185,113,966	-71.86
Combination_3 Rec_BU	185,138,090	-71.86
Combination_4 Rec_BU	185,904,856	-71.74
Bridge_ARIMA_levels Rec_BU	186,311,437	-71.68
Bridge_ARIMA_levels Rec_MinT	187,200,999	-71.54
Combination_3 Rec_WLS	188,091,144	-71.41
Bridge_ARIMA_levels Rec_WLS	190,251,966	-71.08
Combination_4 Rec_WLS	199,679,277	-69.65
Combination_4 Rec_MinT	203,019,031	-69.14

Model	RMSE	Percentage change
Bridge_levels Rec_MinT	351,437,049	-46.58

Additionally, we examined the difference in performance of the best model based on whether the jagged edges have been padded with forecasts or not and the results can be seen in Table 8. As expected, when the full data for the quarter is available, the performance of the model for all sectors are significantly better on average, with the nowcast for the headline GDP's error being 55% lower. This is mainly due to the fact that in the case of forecast padding, any forecast errors for the padded forecast themselves will be carried forward into the errors of the nowcast. This could signify potential room for improvement in the methodology used to pad the jagged edges.

Table 8: Difference in RMSE of the selected best model, based on whether full data is available for the quarter or whether only partial data is available and had been padded with forecasts. Percentage change shows the difference in performance of nowcasts without padding compared to when padded.

Series	Not padded	Padded	Percentage change
GDP at market price	369,156,235	821,389,556	-55.06
Taxes less subsidies	218,053,205	231,574,015	-5.84
Fisheries	27,502,342	130,666,510	-78.95
Wholesale and retail trade	85,170,662	128,812,382	-33.88
Tourism	157,377,509	483,728,922	-67.47
Transportation and communication	153,876,733	168,655,298	-8.76
Financial services	33,558,724	33,184,459	1.13
Construction and real estate	157,419,460	170,491,554	-7.67
Public administration, health and education	60,071,423	60,071,423	0.00
Miscellaneous	89,858,010	91,773,976	-2.09

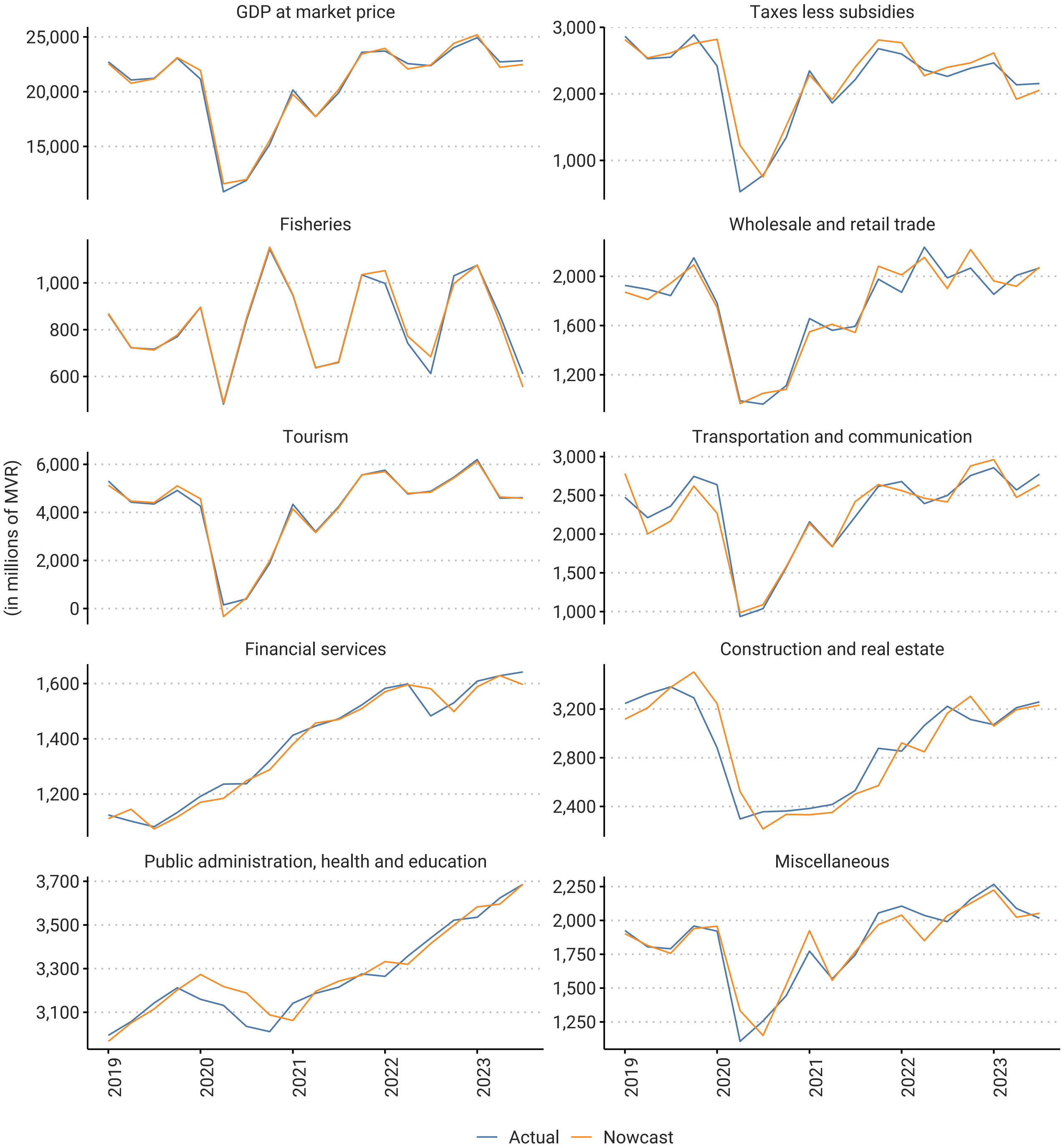
Table 9 below provides details of the selected best model, Combination_3 Rec_BU, including the specific models used to create the combination in addition to the RMSE of the individual models. It can be seen that in series where the relationship between the target variable and the variable used for compilation was very strong and clear (such as the tourism industry), variations of bridge models performed well.

Table 9: The specific models used for each series by the combination, and the model combination's RMSE for the specfic series. Percentage change shows the change in RMSE when compared to the benchmark model, AR1.

Model	Series	RMSE	Percentage change
Bottom-up aggregation	GDP at market price	703,713,467	-82.05
Bridge_ARIMA_levels	Taxes less subsidies	227,156,517	-61.14
Bridge_growth	Fisheries	107,863,884	-42.23
Bridge_ARIMA_growth	Wholesale and retail trade	116,102,399	-59.93
Bridge_ARIMA_levels	Tourism	405,279,747	-72.49
Bridge_ARIMA_levels	Transportation and communication	163,877,259	-66.68
DFM Lasso	Financial services	33,309,681	-95.11
Bridge_ARIMA_levels	Construction and real estate	166,248,435	-74.00
ElasticNet	Public administration, health and education	60,071,423	-54.05
Bridge_ARIMA_levels	Miscellaneous	91,139,796	-75.01

Figure 2 below illustrates the difference in actuals and nowcasts on a sector level for Combination_3 Rec_BU. It can be seen that for headline quarterly GDP and most significant sectors, the model performs well. However, for more volatile industries such as the fisheries industry, there was still some room for improvement. This was likely due to the fact that actual data used in the compilation of some industries of QNA is not publicly available, and the models were unable to capture the dynamic using other variables that were available in our dataset. For example, Maldives Bureau of Statistics (2020) specifies that the main variable used in compiling of the gross value added by the fisheries industry as fish catch, for which the publicly available data ends in December 2021.

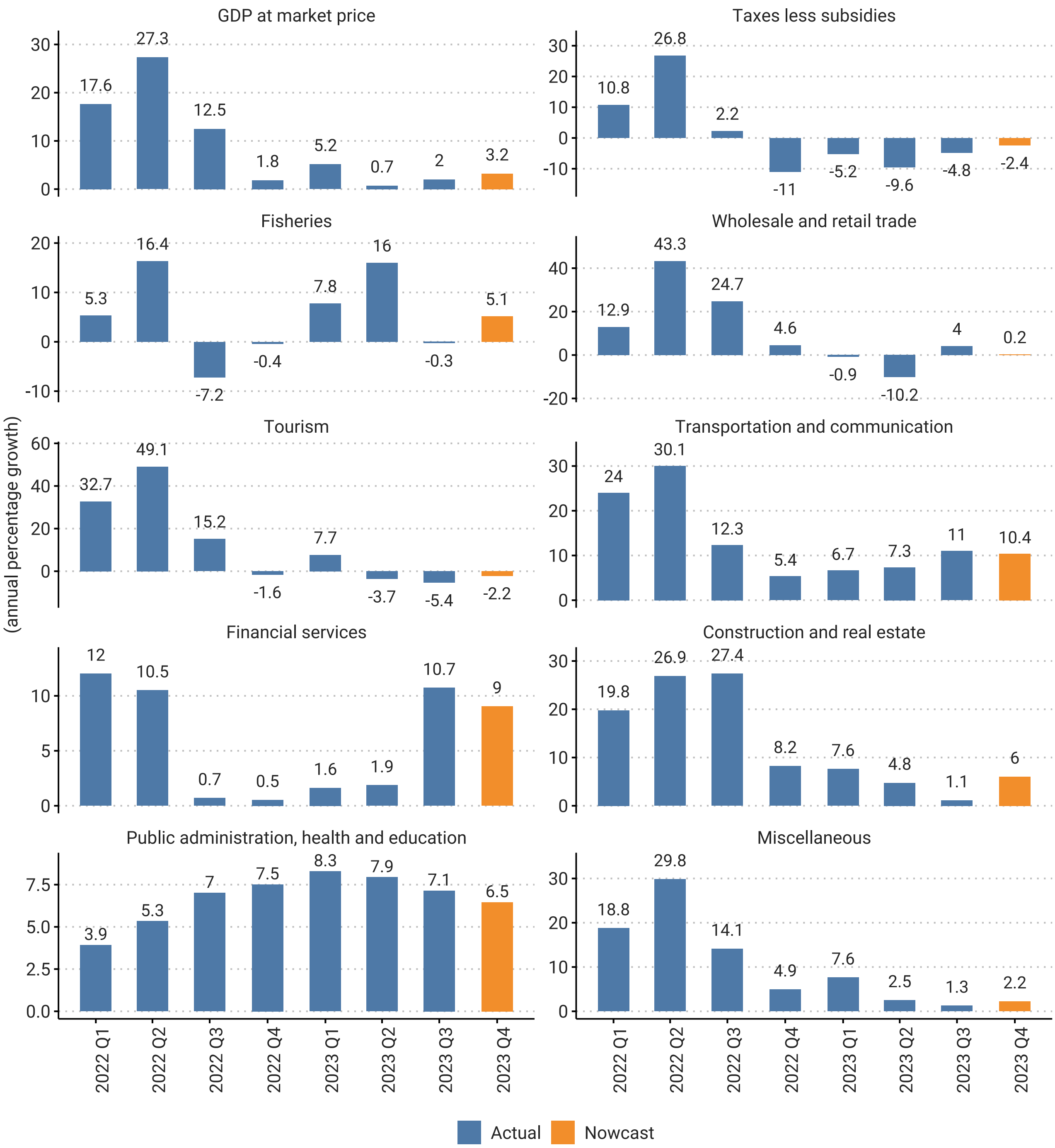
Figure 2: The difference in actuals and nowcasts on a sector level for the best model combination selected. The nowcasts are one step ahead forecasts, with full quarterly data available and no forecast padding of jagged edges.



6 Nowcast

Figure 3 below illustrates the nowcasted annual percentage growth numbers for 2023 Q4 by the selected model, Combination_3 Rec_BU. The model was trained on QNA data until 2023 Q3 and the majority of the explanatory variables were available until December 2023, with some variables lagging and others leading. All missing data and all variables for which data for the full quarter is not available, were treated as described above in preprocessing.

Figure 3: Annual percentage growth numbers based on nowcasts produced by the selected model.



7 Conclusion

In this paper, we explored the nowcasting process for the quarterly GDP using monthly data from multiple sources, both domestic and external. In this process, we used ARIMA models to deal with the jagged edges and K-Nearest Neighbours regressions for any missing data. Additionally, we used multiple univariate and multivariate methods to nowcast the individual series or industries, following which, we used forecast reconciliation methods to ensure the nowcasts adhered to the aggregation constraints.

We believe that there is still room for improvement in the methodology that can and should be explored in future research. Firstly, we showed that there was a significant difference in the nowcasting performance with and without padding in Table 8. This difference could significantly narrow down with methods that forecast the jagged edges better.

Secondly, while K-Nearest Neighbours regression is a standard method of imputation for missing data in practice, it is important to explore whether there could be other methods such as bagging that could outperform it. However, it should be noted that this may result in significant increases in computation time in a process that is already computationally heavy.

Thirdly, currently the hierarchical tree that we have used for forecast reconciliation only has one level. In the future, expanding the hierarchy to include more disaggregated sectors and other levels may significantly improve the performance gain from reconciliation.

Similarly, nowcasting methods could potentially serve to be part of a temporal reconciliation hierarchy that could align short-term and medium-term forecasts. This could be an important avenue to explore when considering the creation of a comprehensive forecasting system that covers nowcasts, short-term forecasts and medium-term forecasts.

Moreover, nowcasting in practice would be carried out with real-time data and therefore, ideally should account for vintages of the quarterly GDP as done in Richardson et al. (2018). However, we decided against it as there are significant revisions that occur in quarterly GDP, which would make it significantly challenging for us to isolate the nowcasting errors due to the model compared to revisions in past data. This issue is illustrated in more detail in Table 14.

Finally, the paper would serve to create a framework to generate nowcasts and conduct experiments for nowcasts for specified periods. It would allow the addition of different methods of forecast padding, imputation and nowcasting fairly easily. Additionally, the framework is flexible as it could be extended to conduct experiments to assess and generate nowcasts alongside forecasts of longer horizons.

In conclusion, this paper can serve to be an important building block for nowcasting and the general forecasting framework in the Maldives. Additionally, we believe that the core issues of nowcasting that we have dealt with in the paper (including but not limited to imputing missing data and padding jagged edges with forecasts), can be an important guideline or starting point for future research. We have also attempted to innovate and add novel contributions to the current global literature on nowcasting by specifying bridge equations with ARIMA errors, the gradient boosting algorithms of XGBoost and LightGBM, model stacking, and by applying reconciliation methods on sector level GDP to tie nowcasts of individual series together.

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Appendix

Table 10: Full list of the explanatory variables used.

ID	Variable	Source	First obs.	Last obs.
104	Total tourist arrivals	Ministry of Tourism	Jan 1988	Dec 2023
105	Arrivals europe	Ministry of Tourism	Jan 1988	Dec 2023
151	Arrivals asia and the pacific	Ministry of Tourism	Jan 1988	Dec 2023
179	Arrivals americas	Ministry of Tourism	Jan 1988	Dec 2023
186	Arrivals middle east	Ministry of Tourism	Jan 2004	Dec 2023
197	Arrivals africa	Ministry of Tourism	Jan 1988	Dec 2023
205	Bed nights	Ministry of Tourism	Jan 1988	Dec 2023
206	Bednights guest houses	Ministry of Tourism	Jan 2010	Dec 2023
207	Bednights hotels	Ministry of Tourism	Jan 2000	Dec 2023
208	Bednights resorts	Ministry of Tourism	Jan 1988	Dec 2023
209	Bednights safari vessels	Ministry of Tourism	Jan 2010	Dec 2023
211	Bed night capacity	Maldives Monetary Authority	Jan 1988	Dec 2023
212	Bedn cap guest houses	Maldives Monetary Authority	Jan 2010	Dec 2023
213	Bedn cap hotels	Maldives Monetary Authority	Jan 2000	Dec 2023
214	Bedn cap resorts	Maldives Monetary Authority	Jan 1988	Dec 2023
215	Bedn cap safari vessels	Maldives Monetary Authority	Jan 2010	Dec 2023
216	Occupancy rate	Ministry of Tourism	Jan 1988	Dec 2023
217	Occr guest houses	Ministry of Tourism	Jan 2000	Dec 2023
218	Occr hotels	Ministry of Tourism	Jan 2000	Dec 2023
219	Occr resorts	Ministry of Tourism	Jan 1988	Dec 2023
220	Occr safari vessels	Ministry of Tourism	Jan 2000	Dec 2023
221	Registered bed capacity	Ministry of Tourism	Jan 2007	Dec 2023
222	Regbedc guest houses	Ministry of Tourism	Jan 2010	Dec 2023

ID	Variable	Source	First obs.	Last obs.
223	Regbedc hotels	Ministry of Tourism	Jan 2007	Dec 2023
224	Regbedc resorts	Ministry of Tourism	Jan 2007	Dec 2023
225	Regbedc safari vessels	Ministry of Tourism	Jan 2010	Dec 2023
226	Operational bed capacity	Ministry of Tourism	Jan 1988	Dec 2023
227	Oprbedc guest houses	Ministry of Tourism	Jan 2010	Dec 2023
228	Oprbedc hotels	Ministry of Tourism	Jan 2000	Dec 2023
229	Oprbedc resorts	Ministry of Tourism	Jan 1988	Dec 2023
230	Oprbedc safari vessels	Ministry of Tourism	Jan 2010	Dec 2023
231	Registered numbers	Ministry of Tourism	Jan 2007	Dec 2023
232	Regnumb guest houses	Ministry of Tourism	Jan 2010	Dec 2023
233	Regnumb hotels	Ministry of Tourism	Jan 2007	Dec 2023
234	Regnumb resorts	Ministry of Tourism	Jan 2007	Dec 2023
235	Regnumb safari vessels	Ministry of Tourism	Jan 2010	Dec 2023
236	Operational numbers	Ministry of Tourism	Jan 2006	Dec 2023
237	Oprnumb guest houses	Ministry of Tourism	Jan 2010	Dec 2023
238	Oprnumb hotels	Ministry of Tourism	Jan 2006	Dec 2023
239	Oprnumb resorts	Ministry of Tourism	Jan 2006	Dec 2023
240	Oprnumb safari vessels	Ministry of Tourism	Jan 2010	Dec 2023
242	Total number of arrival flights	Maldives Airports Company Limited	Jan 2012	Dec 2023
243	Scheduled flights	Maldives Airports Company Limited	Jan 2012	Dec 2023
244	General flights	Maldives Airports Company Limited	Jan 2012	Dec 2023
249	Fish catch	Ministry of Fisheries, Marine Resources and Agriculture	Jan 1995	Dec 2022
250	Fish catch skipjack tuna	Ministry of Fisheries, Marine Resources and Agriculture	Jan 1995	Dec 2022
251	Fish catch yellowfin tuna	Ministry of Fisheries, Marine Resources and Agriculture	Jan 1995	Dec 2022

ID	Variable	Source	First obs.	Last obs.
252	Fish catch other	Ministry of Fisheries, Marine Resources and Agriculture	Jan 1995	Dec 2022
253	Fresh fish purchases	Ministry of Fisheries, Marine Resources and Agriculture	Jan 1995	Dec 2023
254	Fish purchases skipjack tuna	Ministry of Fisheries, Marine Resources and Agriculture	Jan 2012	Dec 2023
255	Fish purchases yellowfin tuna	Ministry of Fisheries, Marine Resources and Agriculture	Jan 2012	Dec 2023
256	Fish purchases other	Ministry of Fisheries, Marine Resources and Agriculture	Jan 2012	Dec 2023
259	Fish prices local iced skipjack tuna	Ministry of Fisheries, Marine Resources and Agriculture	Jan 2014	Dec 2023
260	Fish prices local skipjack tuna	Ministry of Fisheries, Marine Resources and Agriculture	Jan 2014	Dec 2023
261	Fish prices local yellowfin tuna	Ministry of Fisheries, Marine Resources and Agriculture	Jan 2014	Dec 2023
263	Fish prices int bigeye tuna	Ministry of Fisheries, Marine Resources and Agriculture	Feb 2014	Feb 2021
264	Fish prices int skipjack tuna	Ministry of Fisheries, Marine Resources and Agriculture	Jan 2010	Dec 2023
265	Fish prices int yellowfin tuna	Ministry of Fisheries, Marine Resources and Agriculture	Feb 2014	Feb 2021
267	Fish exports	Maldives Customs Service	Jan 2004	Dec 2023
268	Fish exp fresh chilled or frozen tuna	Maldives Customs Service	Jan 2004	Dec 2023

ID	Variable	Source	First obs.	Last obs.
269	Fish exp skipjack tuna	Maldives Customs Service	Jan 2004	Dec 2023
270	Fish exp yellowfin tuna	Maldives Customs Service	Jan 2004	Dec 2023
271	Fish exp other tuna	Maldives Customs Service	Jan 2004	Dec 2023
273	Fish exp canned or pouched fish	Maldives Customs Service	Jan 2004	Dec 2023
274	Fish exp processed fish	Maldives Customs Service	Jan 2004	Dec 2023
280	Cpi total index	Maldives Bureau of Statistics	Jan 1985	Dec 2023
281	Cpi food and non alcoholic beverages	Maldives Bureau of Statistics	Jan 1985	Dec 2023
348	Cpi alcoholic beverages tobacco and narcotics	Maldives Bureau of Statistics	Jun 2004	Dec 2023
356	Cpi clothing and footwear	Maldives Bureau of Statistics	Jan 1985	Dec 2023
374	Cpi housing water electricity gas and other fuels	Maldives Bureau of Statistics	Jan 1985	Dec 2023
393	Cpi furnishing household equipments carpets and other floor coverings	Maldives Bureau of Statistics	Jan 1985	Dec 2023
428	Cpi health	Maldives Bureau of Statistics	Jan 1985	Dec 2023
443	Cpi transport	Maldives Bureau of Statistics	Jan 1987	Dec 2023
464	Cpi information and communication	Maldives Bureau of Statistics	Jun 2004	Dec 2023
483	Cpi recreation sport and culture	Maldives Bureau of Statistics	Jan 1985	Dec 2023
505	Cpi education services	Maldives Bureau of Statistics	Jan 1996	Dec 2023
520	Cpi restaurants and accommodation services	Maldives Bureau of Statistics	Jun 2004	Dec 2023
527	Cpi insurance and financial services	Maldives Bureau of Statistics	Aug 2019	Dec 2023

ID	Variable	Source	First obs.	Last obs.
533	Cpi personal care social protection and miscellaneous goods and services	Maldives Bureau of Statistics	Jan 1996	Dec 2023
1999	Gfs total revenue and grants	Ministry of Finance	Jan 2017	Dec 2023
2000	Gfs tax revenue	Ministry of Finance	Jan 2017	Dec 2023
2001	Gfs import duty	Ministry of Finance	Jan 2017	Dec 2023
2002	Gfs business and property tax	Ministry of Finance	Jan 2017	Dec 2023
2003	Gfs business profit tax	Ministry of Finance	Jan 2017	Dec 2023
2004	Gfs withholding tax	Ministry of Finance	Jan 2017	Dec 2023
2005	Gfs individual income tax	Ministry of Finance	Jan 2017	Dec 2023
2006	Gfs other business and property taxes	Ministry of Finance	Jan 2017	Dec 2023
2007	Gfs goods and services tax	Ministry of Finance	Jan 2017	Dec 2023
2008	Gfs general goods and services tax	Ministry of Finance	Jan 2017	Dec 2023
2009	Gfs tourism goods and services tax	Ministry of Finance	Jan 2017	Dec 2023
2010	Gfs royalties	Ministry of Finance	Jan 2017	Dec 2023
2011	Gfs revenue stamp	Ministry of Finance	Jan 2017	Dec 2023
2012	Gfs green tax	Ministry of Finance	Jan 2017	Dec 2023
2013	Gfs airport service charge	Ministry of Finance	Jan 2017	Dec 2023
2014	Gfs remittance tax	Ministry of Finance	Jan 2017	Dec 2023
2015	Gfs other taxes and duties	Ministry of Finance	Jan 2017	Dec 2023
2016	Gfs non tax revenue	Ministry of Finance	Jan 2017	Dec 2023
2017	Gfs fees and charges	Ministry of Finance	Jan 2017	Dec 2023
2018	Gfs airport development fee	Ministry of Finance	Jan 2017	Dec 2023
2019	Gfs resident permit	Ministry of Finance	Jan 2017	Dec 2023
2020	Gfs other fees and charges	Ministry of Finance	Jan 2017	Dec 2023
2021	Gfs registration and licence fees	Ministry of Finance	Jan 2017	Dec 2023
2022	Gfs property income	Ministry of Finance	Jan 2017	Dec 2023
2023	Gfs rent from resorts	Ministry of Finance	Jan 2017	Dec 2023
2024	Gfs land acquisition and conversion fee	Ministry of Finance	Jan 2017	Dec 2023
2025	Gfs other property income	Ministry of Finance	Jan 2017	Dec 2023
2026	Gfs fines and penalties	Ministry of Finance	Jan 2017	Dec 2023

ID	Variable	Source	First obs.	Last obs.
2027	Gfs interest profit and dividends	Ministry of Finance	Jan 2017	Dec 2023
2028	Gfs soe dividends	Ministry of Finance	Jan 2017	Dec 2023
2029	Gfs interest and profits	Ministry of Finance	Jan 2017	Dec 2023
2030	Gfs other non tax revenues	Ministry of Finance	Jan 2017	Dec 2023
2031	Gfs capital receipts	Ministry of Finance	Jan 2017	Dec 2023
2032	Gfs grants	Ministry of Finance	Jan 2017	Dec 2023
2033	Gfs less subsidiary loan repayment	Ministry of Finance	Jan 2017	Dec 2023
2034	Gfs total recurrent and capital expenditure	Ministry of Finance	Jan 2017	Dec 2023
2035	Gfs recurrent expenditure	Ministry of Finance	Jan 2017	Dec 2023
2036	Gfs salaries wages and pensions	Ministry of Finance	Jan 2017	Dec 2023
2037	Gfs salaries and wages	Ministry of Finance	Jan 2017	Dec 2023
2038	Gfs allowances to employees	Ministry of Finance	Jan 2017	Dec 2023
2039	Gfs pensions retirement benefits and gratuities	Ministry of Finance	Jan 2017	Dec 2023
2040	Gfs pensions	Ministry of Finance	Jan 2017	Dec 2023
2041	Gfs retirement benefits and gratuities	Ministry of Finance	Jan 2017	Dec 2023
2042	Gfs administrative and operational expenses	Ministry of Finance	Jan 2017	Dec 2023
2043	Gfs travelling expenses	Ministry of Finance	Jan 2017	Dec 2023
2044	Gfs administrative supplies	Ministry of Finance	Jan 2017	Dec 2023
2045	Gfs administrative services	Ministry of Finance	Jan 2017	Dec 2023
2046	Gfs operational consumables	Ministry of Finance	Jan 2017	Dec 2023
2047	Gfs training expenses	Ministry of Finance	Jan 2017	Dec 2023
2048	Gfs repairs and maintenance	Ministry of Finance	Jan 2017	Dec 2023
2049	Gfs financing and interest costs	Ministry of Finance	Jan 2017	Dec 2023
2050	Gfs grants contributions and subsidies	Ministry of Finance	Jan 2017	Dec 2023
2051	Gfs aasandha	Ministry of Finance	Jan 2017	Dec 2023
2052	Gfs job seekers allowance	Ministry of Finance	Jan 2017	Dec 2023
2053	Gfs subsidies	Ministry of Finance	Jan 2017	Dec 2023
2054	Gfs grants to councils	Ministry of Finance	Jan 2017	Dec 2023
2055	Gfs tax payments	Ministry of Finance	Jan 2017	Dec 2023
2056	Gfs losses and write offs	Ministry of Finance	Jan 2017	Dec 2023

ID	Variable	Source	First obs.	Last obs.
2057	Gfs capital expenditure	Ministry of Finance	Jan 2017	Dec 2023
2058	Gfs capital equipments	Ministry of Finance	Jan 2017	Dec 2023
2059	Gfs furniture machinery and equipment	Ministry of Finance	Jan 2017	Dec 2023
2060	Gfs vehicles	Ministry of Finance	Jan 2017	Dec 2023
2061	Gfs minor extensions	Ministry of Finance	Jan 2017	Dec 2023
2062	Gfs infrastructure assets	Ministry of Finance	Jan 2017	Dec 2023
2063	Gfs land and buildings	Ministry of Finance	Jan 2017	Dec 2023
2064	Gfs roads bridges and airports	Ministry of Finance	Jan 2017	Dec 2023
2065	Gfs wharves ports and harbours	Ministry of Finance	Jan 2017	Dec 2023
2066	Gfs other infrastructure assets	Ministry of Finance	Jan 2017	Dec 2023
2067	Gfs development projects and investments outlays	Ministry of Finance	Jan 2017	Dec 2023
2068	Gfs development projects	Ministry of Finance	Jan 2017	Dec 2023
2069	Gfs investment outlays	Ministry of Finance	Jan 2017	Dec 2023
2070	Gfs lendings	Ministry of Finance	Jan 2017	Dec 2023
2071	Gfs domestic lendings	Ministry of Finance	Jan 2017	Dec 2023
2072	Gfs foreign lendings	Ministry of Finance	Jan 2017	Dec 2023
2073	Gfs overall balance surplus deficit	Ministry of Finance	Jan 2017	Dec 2023
2074	Gfs primary balance surplus deficit	Ministry of Finance	Jan 2017	Dec 2023
2076	Gfs loan repayment	Ministry of Finance	Jan 2017	Dec 2023
2077	Gfs subscriptions to multilateral agencies	Ministry of Finance	Jan 2017	Dec 2023
2078	Gfs transfers to sovereign development fund	Ministry of Finance	Jan 2017	Dec 2023
2221	Financial 1sg net foreign assets	Maldives Monetary Authority	Jan 1986	Dec 2023
2222	Financial 1sg claims on nonresidents	Maldives Monetary Authority	Jan 1986	Dec 2023
2223	Financial 1sg liabilities to nonresidents	Maldives Monetary Authority	Jan 1986	Dec 2023
2224	Financial 1sg net domestic assets	Maldives Monetary Authority	Jan 1986	Dec 2023
2225	Financial 1sg domestic claims	Maldives Monetary Authority	Jan 1986	Dec 2023

ID	Variable	Source	First obs.	Last obs.
2234	Financial 1sg other items net	Maldives Monetary Authority	Jan 1986	Dec 2023
2244	Financial 1sg monetary base	Maldives Monetary Authority	Jan 1986	Dec 2023
2245	Financial 1sg currency in circulation	Maldives Monetary Authority	Jan 1986	Dec 2023
2246	Financial 1sg liabilities to other depository corporations	Maldives Monetary Authority	Jan 1986	Dec 2023
2247	Financial 1sg liabilities to other sectors	Maldives Monetary Authority	Jan 1986	Dec 2023
2277	Financial 3sg net foreign assets	Maldives Monetary Authority	Jan 1986	Dec 2023
2278	Financial 3sg central bank	Maldives Monetary Authority	Jan 1986	Dec 2023
2281	Financial 3sg other depository corporations	Maldives Monetary Authority	Jan 1986	Dec 2023
2284	Financial 3sg net domestic assets	Maldives Monetary Authority	Jan 1986	Dec 2023
2285	Financial 3sg domestic claims	Maldives Monetary Authority	Jan 1986	Dec 2023
2293	Financial 3sg other items net	Maldives Monetary Authority	Jan 1986	Dec 2023
2299	Financial 3sg broad money	Maldives Monetary Authority	Jan 1986	Dec 2023
2300	Financial 3sg narrow money	Maldives Monetary Authority	Jan 1986	Dec 2023
2303	Financial 3sg quasi money	Maldives Monetary Authority	Jan 1986	Dec 2023
2307	Financial 3sg dollarization ratio	Maldives Monetary Authority	Dec 2001	Dec 2023
2329	Financial 5sg net foreign assets	Maldives Monetary Authority	Jan 2004	Dec 2023
2330	Financial 5sg central bank	Maldives Monetary Authority	Jan 2004	Dec 2023
2333	Financial 5sg other depository corporations	Maldives Monetary Authority	Jan 2004	Dec 2023

ID	Variable	Source	First obs.	Last obs.
2336	Financial 5sg other financial corporations	Maldives Monetary Authority	Jan 2004	Dec 2023
2339	Financial 5sg net domestic assets	Maldives Monetary Authority	Jan 2004	Dec 2023
2340	Financial 5sg domestic claims	Maldives Monetary Authority	Jan 2004	Dec 2023
2347	Financial 5sg other items net	Maldives Monetary Authority	Jan 2004	Dec 2023
2352	Financial 5sg currency outside financial coporations	Maldives Monetary Authority	Jan 2004	Dec 2023
2353	Financial 5sg currency in circulation	Maldives Monetary Authority	Jan 2004	Dec 2023
2354	Financial 5sg currency	Maldives Monetary Authority	Jan 2004	Dec 2023
2355	Financial 5sg deposit	Maldives Monetary Authority	Jan 2004	Dec 2023
2356	Financial 5sg insurance technical reserves	Maldives Monetary Authority	Jan 2004	Dec 2023
2458	Financial total loans and advances	Maldives Monetary Authority	Jan 2008	Dec 2023
2459	Financial credit agriculture	Maldives Monetary Authority	Jan 2008	Dec 2023
2462	Financial credit fishing	Maldives Monetary Authority	Jan 2008	Dec 2023
2469	Financial credit manufacturing	Maldives Monetary Authority	Jan 2008	Dec 2023
2478	Financial credit construction	Maldives Monetary Authority	Jan 2008	Dec 2023
2483	Financial credit real estate	Maldives Monetary Authority	Jan 2008	Dec 2023
2487	Financial credit tourism	Maldives Monetary Authority	Jan 2008	Dec 2023
2493	Financial credit commerce	Maldives Monetary Authority	Jan 2008	Dec 2023
2496	Financial credit transport and communication	Maldives Monetary Authority	Jan 2008	Dec 2023

ID	Variable	Source	First obs.	Last obs.
2499	Financial credit electricity gas water and sanitary services	Maldives Monetary Authority	Jan 2008	Dec 2023
2502	Financial credit personal loans	Maldives Monetary Authority	Jun 2015	Dec 2023
2505	Financial credit other loans and loans not adequately described	Maldives Monetary Authority	Jan 2008	Dec 2023
2707	Trans dep weighted average nc	Maldives Monetary Authority	Jan 2010	Dec 2023
2710	Trans dep weighted average fc	Maldives Monetary Authority	Jan 2010	Dec 2023
2714	Savings dep weighted average nc	Maldives Monetary Authority	Jan 2010	Dec 2023
2717	Savings dep weighted average fc	Maldives Monetary Authority	Jan 2010	Dec 2023
2722	Time dep less3months weighted average nc	Maldives Monetary Authority	Jan 2010	Dec 2023
2725	Time dep less3months weighted average fc	Maldives Monetary Authority	Jan 2010	Dec 2023
2729	Time dep3to6months weighted average nc	Maldives Monetary Authority	Jan 2010	Dec 2023
2732	Time dep3to6months weighted average fc	Maldives Monetary Authority	Jan 2010	Dec 2023
2736	Time dep6mto1year weighted average nc	Maldives Monetary Authority	Jan 2010	Dec 2023
2739	Time dep6mto1year weighted average fc	Maldives Monetary Authority	Jan 2010	Dec 2023
2743	Time dep1to2year weighted average nc	Maldives Monetary Authority	Jan 2010	Dec 2023
2746	Time dep1to2year weighted average fc	Maldives Monetary Authority	Jan 2010	Dec 2023
2750	Time dep2to3year weighted average nc	Maldives Monetary Authority	Jan 2010	Dec 2023
2753	Time dep2to3year weighted average fc	Maldives Monetary Authority	Jan 2010	Dec 2023
2757	Time dep3to5year weighted average nc	Maldives Monetary Authority	Jan 2010	Dec 2023

ID	Variable	Source	First obs.	Last obs.
2760	Time dep3to5year weighted average fc	Maldives Monetary Authority	Feb 2013	Dec 2023
2764	Time dep more5year weighted average nc	Maldives Monetary Authority	Jan 2010	Dec 2023
2767	Time dep more5year weighted average fc	Maldives Monetary Authority	Jan 2010	Dec 2023
2772	Loans pnfc weighted average nc	Maldives Monetary Authority	Jan 2010	Dec 2023
2775	Loans pnfc weighted average fc	Maldives Monetary Authority	Jan 2010	Dec 2023
2779	Loans pvt weighted average nc	Maldives Monetary Authority	Jan 2010	Dec 2023
2782	Loans pvt weighted average fc	Maldives Monetary Authority	Jan 2010	Dec 2023
2785	X1 month mvr treasury bills weighted average	Maldives Monetary Authority	Sep 2006	Dec 2023
2786	X3 month mvr treasury bills weighted average	Maldives Monetary Authority	Sep 2006	Dec 2023
2787	X6 month mvr treasury bills weighted average	Maldives Monetary Authority	Jul 2010	Dec 2023
2788	X1 year mvr treasury bills weighted average	Maldives Monetary Authority	Aug 2012	Dec 2023
2790	Maldives stock exchange index period average	Maldives Stock Exchange Company	May 2002	Dec 2023
2793	Mon pol indicative policy rate	Maldives Monetary Authority	May 2011	Dec 2023
2795	Mrr local currency	Maldives Monetary Authority	Feb 1982	Dec 2023
2796	Mrr foreign currency	Maldives Monetary Authority	Feb 1982	Dec 2023
2799	Reverse repurchase rate 1 week	Maldives Monetary Authority	Aug 2009	Dec 2023
2800	Reverse repurchase rate 2 week	Maldives Monetary Authority	Feb 2011	Apr 2011
2801	Mma repurchase facility rate	Maldives Monetary Authority	Nov 2006	May 2010

ID	Variable	Source	First obs.	Last obs.
2803	Overnight deposit facility	Maldives Monetary Authority	Mar 2010	Dec 2023
3382	Official reserve assets	Maldives Monetary Authority	Jan 1986	Dec 2023
3454	Domestic exports	Maldives Customs Service	Jan 2004	Dec 2023
3455	Dom exp private sector	Maldives Customs Service	Jan 2004	Dec 2023
3456	Dom exp public sector	Maldives Customs Service	Jan 2004	Dec 2023
3457	Imports	Maldives Customs Service	Jan 2004	Dec 2023
3458	Imports private sector	Maldives Customs Service	Jan 2004	Dec 2023
3459	Imports private	Maldives Customs Service	Jan 2004	Dec 2023
3460	Imports tourism	Maldives Customs Service	Jan 2004	Dec 2023
3461	Imports public sector	Maldives Customs Service	Jan 2004	Dec 2023
3462	Imports government	Maldives Customs Service	Jan 2004	Dec 2023
3463	Imports public enterprises	Maldives Customs Service	Jan 2004	Dec 2023
3465	Exports	Gan International Airport; Maamigili International Airport; Maldives Airports Company Limited; Maldives Customs Service	Jan 2004	Dec 2023
3484	Re exports	Gan International Airport; Maamigili International Airport; Maldives Airports Company Limited; Maldives Customs Service	Jan 2004	Dec 2023

ID	Variable	Source	First obs.	Last obs.
3487	Imports food items	Maldives Customs Service	Jan 2004	Dec 2023
3501	Imports furniture fixtures and fittings	Maldives Customs Service	Jan 2004	Dec 2023
3502	Imports electronic and electrical appliances	Maldives Customs Service	Jan 2004	Dec 2023
3503	Imports petroleum products	Maldives Customs Service	Jan 2004	Dec 2023
3508	Imports transport equipments and parts	Maldives Customs Service	Jan 2004	Dec 2023
3509	Imports wood metal cement and aggregates	Maldives Customs Service	Jan 2004	Dec 2023
3513	Imports machinery mechanical appliances and parts	Maldives Customs Service	Jan 2004	Dec 2023
3514	Imports electrical electronic machinery equipments and parts	Maldives Customs Service	Jan 2004	Dec 2023
3515	Imports other items	Maldives Customs Service	Jan 2004	Dec 2023
3516	Imports tobacco and tobacco accessories	Maldives Customs Service	Jan 2004	Dec 2023
3517	Imports personal care and hygiene	Maldives Customs Service	Jan 2004	Dec 2023
3518	Imports stationeries office supplies and printed materials	Maldives Customs Service	Jan 2004	Dec 2023
3519	Imports clothing footwear and fashion accessories	Maldives Customs Service	Jan 2004	Dec 2023
3520	Imports textiles	Maldives Customs Service	Jan 2004	Dec 2023
3521	Imports household items	Maldives Customs Service	Jan 2004	Dec 2023
3522	Imports pharmaceuticals	Maldives Customs Service	Jan 2004	Dec 2023
3523	Imports plastics and articles of plastic	Maldives Customs Service	Jan 2004	Dec 2023
3524	Imports chemical and chemical products	Maldives Customs Service	Jan 2004	Dec 2023

ID	Variable	Source	First obs.	Last obs.
3525	Imports construction related items	Maldives Customs Service	Jan 2004	Dec 2023
3526	Imports medical and surgical supplies	Maldives Customs Service	Jan 2004	Dec 2023
3527	Imports computer equipments and supplies	Maldives Customs Service	Jan 2004	Dec 2023
3528	Imports other items subseries	Maldives Customs Service	Jan 2004	Dec 2023
4061	Mvr per usd average	Maldives Monetary Authority	May 2011	Dec 2023
4062	Mvr per sdr	Maldives Monetary Authority	Jan 1986	Dec 2023
4063	Us dollar per sdr	International Monetary Fund	Jan 1986	Dec 2023
	Crude oil prices	U.S. Energy Information Administration	Jan 1990	Dec 2023
	All commodity price index (pallfnf)	International Monetary Fund	Jan 2003	Dec 2023
	All commodities excluding gold price index (pexgall)	International Monetary Fund	Jan 2003	Dec 2023
	Food and beverage price index (pfandb)	International Monetary Fund	Jan 2003	Dec 2023
	Industrial inputs price index (pindu)	International Monetary Fund	Jan 2003	Dec 2023
	Imports construction related	Constructed	Jan 2004	Dec 2023
	Imports trade related	Constructed	Jan 2004	Dec 2023
	Gfs salaries wages allowances	Constructed	Jan 2017	Dec 2023
	Financial total loans and advances avg	Constructed	Jan 2008	Dec 2023
	Financial 5sg deposit avg	Constructed	Jan 2004	Dec 2023
	Gfs impduty gst subsidies	Constructed	Jan 2017	Dec 2023
	Gfs total revenue and grants cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs tax revenue cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs import duty cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs business and property tax cpi deflated	Constructed	Jan 2017	Dec 2023

ID	Variable	Source	First obs.	Last obs.
	Gfs business profit tax cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs withholding tax cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs individual income tax cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs other business and property taxes cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs goods and services tax cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs general goods and services tax cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs tourism goods and services tax cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs royalties cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs revenue stamp cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs green tax cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs airport service charge cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs remittance tax cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs other taxes and duties cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs non tax revenue cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs fees and charges cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs airport development fee cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs resident permit cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs other fees and charges cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs registration and licence fees cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs property income cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs rent from resorts cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs land acquisition and conversion fee cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs other property income cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs fines and penalties cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs interest profit and dividends cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs soe dividends cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs interest and profits cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs other non tax revenues cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs capital receipts cpi deflated	Constructed	Jan 2017	Dec 2023

ID	Variable	Source	First obs.	Last obs.
	Gfs grants cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs less subsidiary loan repayment cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs total recurrent and capital expenditure cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs recurrent expenditure cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs salaries wages and pensions cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs salaries and wages cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs allowances to employees cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs pensions retirement benefits and gratuities cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs pensions cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs retirement benefits and gratuities cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs administrative and operational expenses cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs travelling expenses cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs administrative supplies cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs administrative services cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs operational consumables cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs training expenses cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs repairs and maintenance cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs financing and interest costs cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs grants contributions and subsidies cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs aasandha cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs job seekers allowance cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs subsidies cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs grants to councils cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs tax payments cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs losses and write offs cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs capital expenditure cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs capital equipments cpi deflated	Constructed	Jan 2017	Dec 2023

ID	Variable	Source	First obs.	Last obs.
	Gfs furniture machinery and equipment cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs vehicles cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs minor extensions cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs infrastructure assets cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs land and buildings cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs roads bridges and airports cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs wharves ports and harbours cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs other infrastructure assets cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs development projects and investments outlays cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs development projects cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs investment outlays cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs lendings cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs domestic lendings cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs foreign lendings cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs overall balance surplus deficit cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs primary balance surplus deficit cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs loan repayment cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs subscriptions to multilateral agencies cpi deflated	Constructed	Jan 2017	Dec 2023
	Gfs transfers to sovereign development fund cpi deflated	Constructed	Jan 2017	Dec 2023
	Financial 1sg net foreign assets cpi deflated	Constructed	Jan 1986	Dec 2023
	Financial 1sg claims on nonresidents cpi deflated	Constructed	Jan 1986	Dec 2023
	Financial 1sg liabilities to nonresidents cpi deflated	Constructed	Jan 1986	Dec 2023
	Financial 1sg net domestic assets cpi deflated	Constructed	Jan 1986	Dec 2023
	Financial 1sg domestic claims cpi deflated	Constructed	Jan 1986	Dec 2023
	Financial 1sg other items net cpi deflated	Constructed	Jan 1986	Dec 2023
	Financial 1sg monetary base cpi deflated	Constructed	Jan 1986	Dec 2023

ID	Variable	Source	First obs.	Last obs.
	Financial 1sg currency in circulation cpi deflated	Constructed	Jan 1986	Dec 2023
	Financial 1sg liabilities to other depository corporations cpi deflated	Constructed	Jan 1986	Dec 2023
	Financial 1sg liabilities to other sectors cpi deflated	Constructed	Jan 1986	Dec 2023
	Financial 3sg net foreign assets cpi deflated	Constructed	Jan 1986	Dec 2023
	Financial 3sg central bank cpi deflated	Constructed	Jan 1986	Dec 2023
	Financial 3sg other depository corporations cpi deflated	Constructed	Jan 1986	Dec 2023
	Financial 3sg net domestic assets cpi deflated	Constructed	Jan 1986	Dec 2023
	Financial 3sg domestic claims cpi deflated	Constructed	Jan 1986	Dec 2023
	Financial 3sg other items net cpi deflated	Constructed	Jan 1986	Dec 2023
	Financial 3sg broad money cpi deflated	Constructed	Jan 1986	Dec 2023
	Financial 3sg narrow money cpi deflated	Constructed	Jan 1986	Dec 2023
	Financial 3sg quasi money cpi deflated	Constructed	Jan 1986	Dec 2023
	Financial 3sg dollarization ratio cpi deflated	Constructed	Dec 2001	Dec 2023
	Financial 5sg net foreign assets cpi deflated	Constructed	Jan 2004	Dec 2023
	Financial 5sg central bank cpi deflated	Constructed	Jan 2004	Dec 2023
	Financial 5sg other depository corporations cpi deflated	Constructed	Jan 2004	Dec 2023
	Financial 5sg other financial corporations cpi deflated	Constructed	Jan 2004	Dec 2023
	Financial 5sg net domestic assets cpi deflated	Constructed	Jan 2004	Dec 2023
	Financial 5sg domestic claims cpi deflated	Constructed	Jan 2004	Dec 2023
	Financial 5sg other items net cpi deflated	Constructed	Jan 2004	Dec 2023
	Financial 5sg currency outside financial coporations cpi deflated	Constructed	Jan 2004	Dec 2023
	Financial 5sg currency in circulation cpi deflated	Constructed	Jan 2004	Dec 2023
	Financial 5sg currency cpi deflated	Constructed	Jan 2004	Dec 2023
	Financial 5sg deposit cpi deflated	Constructed	Jan 2004	Dec 2023
	Financial 5sg insurance technical reserves cpi deflated	Constructed	Jan 2004	Dec 2023

ID	Variable	Source	First obs.	Last obs.
	Financial total loans and advances cpi deflated	Constructed	Jan 2008	Dec 2023
	Financial credit agriculture cpi deflated	Constructed	Jan 2008	Dec 2023
	Financial credit fishing cpi deflated	Constructed	Jan 2008	Dec 2023
	Financial credit manufacturing cpi deflated	Constructed	Jan 2008	Dec 2023
	Financial credit construction cpi deflated	Constructed	Jan 2008	Dec 2023
	Financial credit real estate cpi deflated	Constructed	Jan 2008	Dec 2023
	Financial credit tourism cpi deflated	Constructed	Jan 2008	Dec 2023
	Financial credit commerce cpi deflated	Constructed	Jan 2008	Dec 2023
	Financial credit transport and communication cpi deflated	Constructed	Jan 2008	Dec 2023
	Financial credit electricity gas water and sanitary services cpi deflated	Constructed	Jan 2008	Dec 2023
	Financial credit personal loans cpi deflated	Constructed	Jun 2015	Dec 2023
	Financial credit other loans and loans not adequately described cpi deflated	Constructed	Jan 2008	Dec 2023
	Domestic exports cpi deflated	Constructed	Jan 2004	Dec 2023
	Dom exp private sector cpi deflated	Constructed	Jan 2004	Dec 2023
	Dom exp public sector cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports private sector cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports private cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports tourism cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports public sector cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports government cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports public enterprises cpi deflated	Constructed	Jan 2004	Dec 2023
	Exports cpi deflated	Constructed	Jan 2004	Dec 2023
	Re exports cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports food items cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports furniture fixtures and fittings cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports electronic and electrical appliances cpi deflated	Constructed	Jan 2004	Dec 2023

ID	Variable	Source	First obs.	Last obs.
	Imports petroleum products cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports transport equipments and parts cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports wood metal cement and aggregates cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports machinery mechanical appliances and parts cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports electrical electronic machinery equipments and parts cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports other items cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports tobacco and tobacco accessories cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports personal care and hygiene cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports stationeries office supplies and printed materials cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports clothing footwear and fashion accessories cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports textiles cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports household items cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports pharmaceuticals cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports plastics and articles of plastic cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports chemical and chemical products cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports construction related items cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports medical and surgical supplies cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports computer equipments and supplies cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports other items subseries cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports construction related cpi deflated	Constructed	Jan 2004	Dec 2023
	Imports trade related cpi deflated	Constructed	Jan 2004	Dec 2023
	Gfs salaries wages allowances cpi deflated	Constructed	Jan 2017	Dec 2023

ID	Variable	Source	First obs.	Last obs.
	Financial total loans and advances avg cpi deflated	Constructed	Jan 2008	Dec 2023
	Financial 5sg deposit avg cpi deflated	Constructed	Jan 2004	Dec 2023
	Gfs impduty gst subsidies cpi deflated	Constructed	Jan 2017	Dec 2023
	Imports construction related pindu deflated	Constructed	Jan 2004	Dec 2023

ID refers to the series ID in the Maldives Monetary Authority database (database.mma.gov.mv). It is left blank if the variable is either from an external source or if it is a variable created by us.

Table 11: RMSE of all models for all series (both headline GDP and sectors) for the forecast horizon of one quarter ahead. Percentage change shows the change in RMSE when compared to the benchmark model, AR1.

Model	RMSE	Percentage change
Combination_3 Rec_BU	283,495,618	-79.57
Bridge_ARIMA_levels Rec_BU	285,392,102	-79.44
Bridge_ARIMA_levels Rec_MinT	288,003,877	-79.25
Combination_3 Rec_MinT	288,355,283	-79.22
Combination_4 Rec_BU	289,294,066	-79.16
Bridge_ARIMA_levels Rec_WLS	296,245,751	-78.66
Combination_3 Rec_WLS	301,402,949	-78.28
Combination_4 Rec_WLS	316,497,208	-77.20
Combination_4 Rec_MinT	316,563,543	-77.19
Bridge_levels Rec_MinT	556,356,860	-59.92
Bridge_levels Rec_BU	562,388,536	-59.48
UMIDAS_levels Rec_MinT	585,692,213	-57.80
UMIDAS_levels Rec_BU	587,897,515	-57.64
RMIDAS_levels Rec_MinT	592,359,513	-57.32
RMIDAS_levels Rec_BU	594,399,667	-57.17
Bridge_levels Rec_WLS	659,664,990	-52.47
RMIDAS_levels Rec_WLS	679,835,136	-51.02
UMIDAS_levels Rec_WLS	680,330,229	-50.98
Ridge Rec_MinT	712,520,660	-48.66
Ridge Rec_WLS	717,226,122	-48.32
Ridge Rec_BU	745,285,568	-46.30
XGBoost Rec_WLS	829,383,163	-40.24
XGBoost Rec_MinT	829,525,097	-40.23
RandomForest Rec_BU	830,623,702	-40.15
RandomForest Rec_WLS	849,581,509	-38.79
RandomForest Rec_MinT	851,500,947	-38.65
XGBoost Rec_BU	865,979,415	-37.61
LightGBM Rec_WLS	878,666,883	-36.69

Model	RMSE	Percentage change
LightGBM Rec_MinT	881,036,903	-36.52
LightGBM Rec_BU	893,326,203	-35.64
SupportVector Rec_WLS	904,289,563	-34.85
SupportVector Rec_MinT	906,083,510	-34.72
SupportVector Rec_BU	922,600,919	-33.53
DFM2 Rec_MinT	923,400,568	-33.47
DFM2 Rec_WLS	923,400,568	-33.47
DFM2 Rec_BU	923,400,568	-33.47
Model_Stack Rec_WLS	933,988,243	-32.71
DFM1 Rec_MinT	941,861,268	-32.14
DFM1 Rec_BU	941,861,268	-32.14
DFM1 Rec_WLS	941,861,268	-32.14
DFM Combined Rec_BU	944,324,406	-31.96
DFM Combined Rec_WLS	944,324,406	-31.96
DFM Combined Rec_MinT	944,324,406	-31.96
ElasticNet Rec_WLS	974,157,242	-29.81
Model_Stack Rec_MinT	982,978,829	-29.18
ETS Rec_WLS	985,594,560	-28.99
ETS Rec_MinT	988,063,902	-28.81
ETS Rec_BU	993,501,281	-28.42
ElasticNet Rec_MinT	1,001,060,621	-27.87
ElasticNet Rec_BU	1,051,857,157	-24.22
Lasso Rec_WLS	1,076,940,911	-22.41
Model_Stack Rec_BU	1,089,631,652	-21.49
Lasso Rec_MinT	1,110,344,884	-20.00
Thief Rec_WLS	1,137,522,784	-18.04
Thief Rec_MinT	1,141,063,850	-17.79
AutoARIMA Rec_BU	1,154,669,985	-16.81
Thief Rec_BU	1,162,528,009	-16.24
Lasso Rec_BU	1,168,114,035	-15.84

Model	RMSE	Percentage change
AutoARIMA Rec_WLS	1,175,270,836	-15.32
DFM Lasso Rec_MinT	1,181,290,273	-14.89
DFM Lasso Rec_BU	1,181,290,273	-14.89
DFM Lasso Rec_WLS	1,181,290,273	-14.89
AutoARIMA Rec_MinT	1,203,798,981	-13.27
AR1 Rec_WLS	1,332,517,143	-3.99
AR1 Rec_BU	1,341,069,133	-3.38
AR1 Rec_MinT	1,358,540,508	-2.12
AR1	1,387,952,000	0.00
NNETAR Rec_WLS	1,644,038,652	18.45
NNETAR Rec_MinT	1,677,889,264	20.89
Combination_2 Rec_MinT	4,072,117,668	193.39
Combination_1 Rec_WLS	4,093,409,650	194.92
Combination_2 Rec_WLS	4,280,476,232	208.40
Combination_1 Rec_MinT	4,687,224,185	237.71
Combination_1 Rec_BU	5,643,588,545	306.61
Combination_2 Rec_BU	11,937,758,522	760.10
NNETAR Rec_BU	19,371,005,266	1,295.65
UMIDAS_growth Rec_WLS	125,502,609,111	8,942.29
UMIDAS_growth Rec_MinT	127,726,027,757	9,102.48
UMIDAS_growth Rec_BU	157,116,912,810	11,220.05
Bridge_ARIMA_growth Rec_WLS	196,975,029,784	14,091.78
Bridge_growth Rec_WLS	202,765,392,388	14,508.96
Bridge_ARIMA_growth Rec_MinT	209,997,799,166	15,030.05
Bridge_ARIMA_growth Rec_BU	213,364,007,439	15,272.58
Bridge_growth Rec_MinT	218,447,764,039	15,638.86
Bridge_growth Rec_BU	221,280,942,552	15,842.98
RMIDAS_growth Rec_WLS	1,097,723,893,134	78,989.47
RMIDAS_growth Rec_MinT	1,115,750,737,732	80,288.28
RMIDAS_growth Rec_BU	1,324,508,165,196	95,328.96

Table 12: RMSE of all models for headline quarterly GDP for the forecast horizon of one quarter ahead. Percentage change shows the change in RMSE when compared to the benchmark model, AR1.

Model	RMSE	Percentage change
Combination_3 Rec_BU	703,713,467	-82.05
Bridge_ARIMA_levels Rec_BU	708,575,299	-81.93
Bridge_ARIMA_levels Rec_MinT	716,982,850	-81.71
Combination_3 Rec_MinT	723,244,818	-81.55
Combination_4 Rec_BU	725,165,517	-81.50
Bridge_ARIMA_levels Rec_WLS	742,868,195	-81.05
Combination_3 Rec_WLS	768,135,973	-80.41
Combination_4 Rec_MinT	794,464,741	-79.73
Combination_4 Rec_WLS	801,784,575	-79.55
Bridge_levels Rec_MinT	1,408,459,288	-64.07
Bridge_levels Rec_BU	1,419,559,760	-63.79
UMIDAS_levels Rec_BU	1,472,744,958	-62.43
UMIDAS_levels Rec_MinT	1,474,791,759	-62.38
RMIDAS_levels Rec_BU	1,491,624,848	-61.95
RMIDAS_levels Rec_MinT	1,497,464,398	-61.80
Combination_2 Rec_MinT	1,669,203,695	-57.42
Bridge_levels Rec_WLS	1,772,136,493	-54.80
UMIDAS_levels Rec_WLS	1,814,079,285	-53.73
RMIDAS_levels Rec_WLS	1,814,326,441	-53.72
Model_Stack Rec_WLS	1,949,519,021	-50.27
Ridge Rec_MinT	1,950,713,559	-50.24
Ridge Rec_WLS	1,958,385,522	-50.05
Ridge Rec_BU	2,026,256,224	-48.31
Model_Stack Rec_MinT	2,103,972,709	-46.33
RandomForest Rec_BU	2,304,492,727	-41.22
XGBoost Rec_WLS	2,311,660,219	-41.03
XGBoost Rec_MinT	2,313,303,327	-40.99
RandomForest Rec_WLS	2,364,524,810	-39.69

Model	RMSE	Percentage change
RandomForest Rec_MinT	2,369,045,107	-39.57
XGBoost Rec_BU	2,413,764,323	-38.43
ElasticNet Rec_WLS	2,422,003,105	-38.22
LightGBM Rec_WLS	2,456,597,274	-37.34
LightGBM Rec_MinT	2,462,535,129	-37.19
ElasticNet Rec_MinT	2,505,833,904	-36.08
LightGBM Rec_BU	2,510,473,367	-35.96
SupportVector Rec_WLS	2,519,835,544	-35.72
SupportVector Rec_MinT	2,522,464,471	-35.66
SupportVector Rec_BU	2,582,513,751	-34.13
DFM2 Rec_MinT	2,591,627,802	-33.89
DFM2 Rec_WLS	2,591,627,802	-33.89
DFM2 Rec_BU	2,591,627,802	-33.89
Model_Stack Rec_BU	2,615,628,003	-33.28
DFM1 Rec_MinT	2,645,906,479	-32.51
DFM1 Rec_BU	2,645,906,479	-32.51
DFM1 Rec_WLS	2,645,906,479	-32.51
Lasso Rec_WLS	2,653,342,572	-32.32
DFM Combined Rec_MinT	2,654,304,007	-32.29
DFM Combined Rec_BU	2,654,304,007	-32.29
DFM Combined Rec_WLS	2,654,304,007	-32.29
ElasticNet Rec_BU	2,655,588,026	-32.26
ETS Rec_WLS	2,756,998,011	-29.67
Lasso Rec_MinT	2,759,780,090	-29.60
ETS Rec_MinT	2,763,928,055	-29.50
ETS Rec_BU	2,780,844,072	-29.07
Lasso Rec_BU	2,939,878,056	-25.01
AutoARIMA Rec_BU	3,080,820,736	-21.41
AutoARIMA Rec_WLS	3,081,956,166	-21.39
AutoARIMA Rec_MinT	3,135,758,960	-20.01

Model	RMSE	Percentage change
Thief Rec_WLS	3,145,812,386	-19.76
Thief Rec_MinT	3,157,083,350	-19.47
Thief Rec_BU	3,211,075,569	-18.09
DFM Lasso Rec_MinT	3,316,453,474	-15.40
DFM Lasso Rec_BU	3,316,453,474	-15.40
DFM Lasso Rec_WLS	3,316,453,474	-15.40
Combination_1 Rec_MinT	3,673,058,511	-6.31
AR1 Rec_WLS	3,730,758,948	-4.84
AR1 Rec_BU	3,753,624,340	-4.25
AR1 Rec_MinT	3,813,380,016	-2.73
AR1	3,920,349,351	0.00
NNETAR Rec_WLS	4,072,191,060	3.87
NNETAR Rec_MinT	4,162,828,512	6.19
Combination_2 Rec_WLS	4,180,929,355	6.65
Combination_1 Rec_WLS	5,005,516,858	27.68
Combination_1 Rec_BU	15,134,029,886	286.04
Combination_2 Rec_BU	31,619,309,156	706.54
NNETAR Rec_BU	43,262,802,850	1,003.54
UMIDAS_growth Rec_WLS	139,519,506,000	3,458.85
UMIDAS_growth Rec_MinT	175,739,647,281	4,382.75
UMIDAS_growth Rec_BU	334,129,264,370	8,422.95
Bridge_ARIMA_growth Rec_WLS	408,541,212,722	10,321.04
Bridge_growth Rec_WLS	422,815,011,842	10,685.14
Bridge_ARIMA_growth Rec_MinT	469,246,288,098	11,869.50
Bridge_ARIMA_growth Rec_BU	484,611,529,299	12,261.44
Bridge_growth Rec_MinT	492,252,493,751	12,456.34
Bridge_growth Rec_BU	506,089,725,698	12,809.30
RMIDAS_growth Rec_WLS	1,854,000,017,187	47,191.70
RMIDAS_growth Rec_MinT	2,008,181,159,679	51,124.55
RMIDAS_growth Rec_BU	2,979,707,792,857	75,906.18

Table 13: RMSE of all models for the sectors of GDP (bottom level series) for the forecast horizon of one quarter ahead. Percentage change shows the change in RMSE when compared to the benchmark model, AR1.

Model	RMSE	Percentage change
Combination_3 Rec_MinT	185,113,966	-71.86
Combination_3 Rec_BU	185,138,090	-71.86
Combination_4 Rec_BU	185,904,856	-71.74
Bridge_ARIMA_levels Rec_BU	186,311,437	-71.68
Bridge_ARIMA_levels Rec_MinT	187,200,999	-71.54
Combination_3 Rec_WLS	188,091,144	-71.41
Bridge_ARIMA_levels Rec_WLS	190,251,966	-71.08
Combination_4 Rec_WLS	199,679,277	-69.65
Combination_4 Rec_MinT	203,019,031	-69.14
Bridge_levels Rec_MinT	351,437,049	-46.58
Bridge_levels Rec_BU	357,096,119	-45.72
Bridge_levels Rec_WLS	366,834,998	-44.24
UMIDAS_levels Rec_MinT	373,473,628	-43.23
RMIDAS_levels Rec_MinT	375,129,355	-42.98
Ridge Rec_MinT	375,880,230	-42.86
UMIDAS_levels Rec_BU	378,191,188	-42.51
RMIDAS_levels Rec_BU	381,250,130	-42.05
Ridge Rec_WLS	381,351,289	-42.03
RMIDAS_levels Rec_WLS	384,415,528	-41.57
UMIDAS_levels Rec_WLS	385,516,761	-41.40
Ridge Rec_BU	401,219,183	-39.01
XGBoost Rec_MinT	412,276,414	-37.33
XGBoost Rec_WLS	412,982,558	-37.22
RandomForest Rec_BU	420,141,591	-36.13
RandomForest Rec_WLS	425,167,918	-35.37
RandomForest Rec_MinT	426,635,924	-35.15
XGBoost Rec_BU	431,141,286	-34.46
LightGBM Rec_BU	431,771,612	-34.37

Model	RMSE	Percentage change
LightGBM Rec_WLS	432,779,742	-34.21
LightGBM Rec_MinT	434,380,911	-33.97
DFM2 Rec_MinT	448,472,894	-31.83
DFM2 Rec_WLS	448,472,894	-31.83
DFM2 Rec_BU	448,472,894	-31.83
SupportVector Rec_WLS	450,656,923	-31.50
SupportVector Rec_BU	452,468,203	-31.22
SupportVector Rec_MinT	453,020,268	-31.14
DFM1 Rec_MinT	455,851,509	-30.71
DFM1 Rec_BU	455,851,509	-30.71
DFM1 Rec_WLS	455,851,509	-30.71
DFM Combined Rec_WLS	456,089,182	-30.67
DFM Combined Rec_BU	456,089,182	-30.67
DFM Combined Rec_MinT	456,089,182	-30.67
ETS Rec_WLS	484,530,509	-26.35
ETS Rec_MinT	485,730,201	-26.16
ETS Rec_BU	487,323,096	-25.92
DFM Lasso Rec_MinT	573,062,285	-12.89
DFM Lasso Rec_BU	573,062,285	-12.89
DFM Lasso Rec_WLS	573,062,285	-12.89
Thief Rec_WLS	581,515,765	-11.60
Thief Rec_MinT	582,436,626	-11.46
Thief Rec_BU	596,630,112	-9.31
ElasticNet Rec_WLS	634,536,075	-3.54
ElasticNet Rec_MinT	644,810,060	-1.98
AR1 Rec_WLS	652,980,947	-0.74
AutoARIMA Rec_BU	653,296,881	-0.69
AR1	657,855,818	0.00
AR1 Rec_BU	657,855,818	0.00
AR1 Rec_MinT	659,499,472	0.25

Model	RMSE	Percentage change
ElasticNet Rec_BU	667,656,517	1.49
AutoARIMA Rec_WLS	692,351,995	5.24
Lasso Rec_WLS	711,632,743	8.17
AutoARIMA Rec_MinT	719,439,258	9.36
Lasso Rec_MinT	723,592,232	9.99
Model_Stack Rec_WLS	739,573,147	12.42
Lasso Rec_BU	745,506,614	13.32
Model_Stack Rec_BU	747,697,319	13.66
Model_Stack Rec_MinT	762,727,024	15.94
NNETAR Rec_WLS	1,077,336,782	63.76
NNETAR Rec_MinT	1,096,660,720	66.70
Combination_1 Rec_BU	3,152,812,785	379.26
Combination_1 Rec_WLS	3,979,179,517	504.87
Combination_2 Rec_MinT	4,256,174,365	546.98
Combination_2 Rec_WLS	4,291,394,457	552.33
Combination_1 Rec_MinT	4,786,663,728	627.62
Combination_2 Rec_BU	6,874,429,865	944.98
NNETAR Rec_BU	14,455,634,580	2,097.39
UMIDAS_growth Rec_MinT	121,222,915,894	18,326.97
UMIDAS_growth Rec_BU	122,571,918,843	18,532.03
UMIDAS_growth Rec_WLS	123,847,287,855	18,725.90
Bridge_ARIMA_growth Rec_BU	156,487,011,309	23,687.43
Bridge_ARIMA_growth Rec_MinT	156,630,732,635	23,709.28
Bridge_ARIMA_growth Rec_WLS	156,732,504,284	23,724.75
Bridge_growth Rec_WLS	160,681,019,159	24,324.96
Bridge_growth Rec_BU	161,081,671,800	24,385.86
Bridge_growth Rec_MinT	161,548,664,334	24,456.85
RMIDAS_growth Rec_MinT	967,023,239,833	146,896.23
RMIDAS_growth Rec_WLS	978,244,538,381	148,601.97
RMIDAS_growth Rec_BU	981,187,504,217	149,049.32

Table 14: Revisions in GDP, computed by comparing growth published in the first estimate and second estimate.

Date	GDP	Taxes less subsidies	Fisheries	Trade	Tourism	Financial services	Transp. & comm.	Cons. & real est.	Pub., hlth. & educ.	Misc.
2017 Q4	0.2	0.1	0.0	6.3	0.0	-25.6	0.7	5.1	0.1	-2.0
2018 Q1	-2.2	-5.1	5.8	-3.7	-2.3	2.2	-1.2	-6.9	1.3	-3.2
2018 Q2	1.7	2.7	0.1	9.6	-0.3	0.1	1.4	1.6	0.0	2.2
2018 Q3	-3.5	-2.8	0.0	-21.1	0.0	-0.1	-2.2	-4.5	0.0	-4.6
2018 Q4	1.0	-3.6	14.9	6.3	-0.1	0.0	4.0	-1.2	-0.4	-0.1
2019 Q1	1.6	21.6	-2.1	-11.9	-2.0	-8.0	-0.5	9.0	2.2	-2.3
2019 Q2	-1.7	-20.9	0.0	2.1	0.0	-0.3	0.2	-0.1	0.0	0.5
2019 Q3	-0.9	-1.3	0.0	-9.8	0.0	0.0	1.0	-0.1	0.0	-1.0
2019 Q4	0.7	2.3	4.8	7.4	0.0	0.0	0.9	-3.7	0.0	1.1
2020 Q1	1.0	1.0	0.1	8.1	-0.8	-3.4	-4.3	8.9	1.5	-1.1
2020 Q2	-0.4	0.0	16.4	-1.6	0.1	0.0	-6.3	-1.2	0.3	0.4
2020 Q3	0.0	-0.4	1.8	1.3	0.0	0.0	-0.6	-0.6	0.0	0.4
2020 Q4	-5.6	-10.0	0.0	-22.3	0.0	0.0	-5.0	-13.4	-0.1	-5.4
2021 Q1	-1.5	-8.0	21.5	11.9	-3.8	-4.6	0.3	-3.5	-4.7	2.4
2021 Q2	-3.6	32.5	0.0	-10.3	-3.5	0.0	-0.9	4.0	-9.5	-1.4
2021 Q3	0.9	-0.8	32.1	-2.6	7.9	0.2	1.9	0.4	-0.4	-12.6
2021 Q4	0.2	0.0	0.0	0.0	0.0	2.0	0.5	0.0	0.0	0.0
2022 Q1	3.2	2.6	22.3	40.6	0.7	8.0	3.2	-7.7	-13.5	12.9

Date	GDP	Taxes less subsidies	Fisheries	Trade	Tourism	Financial services	Transp. & comm.	Cons. & real est.	Pub., hlth. & educ.	Misc.
2022 Q2	-4.3	-5.6	0.0	-0.4	0.0	0.1	-0.1	-26.8	0.0	-2.2
2022 Q3	-2.3	-12.0	-7.0	-39.8	3.5	-0.2	-10.1	26.7	-3.5	-6.1
2022 Q4	0.0	0.0	0.0	0.0	0.0	-0.2	0.4	0.0	-0.2	0.0
2023 Q1	-1.1	-9.7	0.4	1.6	-3.4	-0.8	-0.1	0.8	5.0	3.0
2023 Q2	0.7	1.0	0.0	1.3	0.6	0.1	0.7	1.9	0.1	0.0

Revisions generally follow for longer periods, but for ease of tabulation and as nowcasting is related to near-term estimates, only the first and second estimates are compared.

Highlighted based on absolute difference in growth—5 percentage points, 10 percentage points, 15 percentage points or more.

As GDP was rebased in 2023 Q2, the growth rate for 2023 Q1 shows the difference in the growth rates before and after rebasing.