Exploring Nowcasting Techniques for Real-Time GDP Estimation in Bhutan

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30 June 2024

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Abstract

In various policy institutions, current estimates of quarterly GDP growth are frequently employed to advise decision makers on the current state of the economy. The bridge equation serves as a fundamental model for nowcasting, elucidating GDP growth through the utilization of time-aggregated business cycle indicators. Recent academic literature has shown significant interest in an alternative method for nowcasting known as mixed-data sampling, abbreviated as MIDAS. Given this context, the paper examines the following questions: How can we estimate annual GDP of Bhutan through MIDAS and bridge equations? Do they matter for nowcasting GDP growth in practice? By addressing these questions, the study aims to provide insights into the application and comparative efficacy of these nowcasting techniques in an empirical context.

Keywords: Bridge equations, Mixed-data Sampling (MIDAS), GDP, nowcasting.

1. Introduction

During major economic downturns, such as the COVID-19 pandemic or the global financial crisis, governments often implement counter-cyclical policies. These are measures designed to counteract the negative economic cycle. The goal of counter-cyclical policies is to mitigate the severity of the shock to a country's real gross domestic product (GDP). However, implementing effective counter-cyclical policies relies on timely economic data. Unfortunately, such data can be difficult to obtain due to two main issues. First, there can be gaps in data collection and publication, especially for real GDP – this is known as the ‘ragged-edge’ problem (Wallis, 1986). Second, key economic indicators might be released at different times or intervals, making it difficult to compare them accurately (Armesto, Engemann & Owyan, 2010). As a result, evaluating macroeconomic conditions in real time becomes challenging.

Bhutan, a small developing economy, opts for a blended approach to economic progress, balancing the pursuit of both Gross National Happiness (GNH) and Gross Domestic Product (Thinley, 2012) . While national happiness is measured periodically through surveys centred around the nine domains, GDP is accounted annually and published with a significant delay of six to nine months (Gross National Happiness Centre, 2016). The unavailability of key macroeconomic variables at frequencies higher than quarterly has led to many macroeconomic models being specified on annual data.

Policymakers need a way to understand the current state of the economy as it unfolds, even when complete data is not available (Lewis et al., 2020). Major economic shocks like the 2008 financial crisis, COVID-19, and climate events require swift policy responses. However, data deficiencies and publication delays create significant hurdles for timely decision-making. One such challenge is the inconsistent frequency at which key economic data is collected. Unlike traditional forecasting tools, which assume data is gathered at the same intervals, real-world data often arrives at different times (Ferrara, Guegan, & Rakotomarolahy, 2010). This uneven sampling creates unbalanced datasets and makes it difficult to get a clear picture of the current economic state.

Nowcasting is particularly relevant for Bhutan's current economic challenges. Since most high-frequency economic indicators are only published annually with a significant delay, it is difficult to develop real-time policy responses based on the evolving economic situation. Nowcasting offers a way to bridge this gap by using more frequently available data to make near-term predictions (Den Reijer & Johansson, 2019, p. 1351). This paper compares two single-equation approaches for nowcasting: i) Mixed-data Sampling (MIDAS) and ii) Bridge equations.

The MIDAS uses a distributed lag polynomials to deal with mixed frequency data but also achieve parsimonious specification due to tight parameterization (Foroni et al., 2017). The MIDAS approach offers several advantages over bridge equations, enhancing prediction accuracy. Firstly, unlike bridge equations which rely on iterated forecasts, MIDAS serves as a direct multi-step nowcasting tool. Secondly, in bridge equations, the weights of indicator observations are partially fixed due to time aggregation, whereas MIDAS equations utilize empirical weighting of high-frequency predictor observations with estimated functional lag polynomials (Schumacher, 2016).

Bridge equations are dynamic, although they explain the low-frequency variable through low-frequency lags of a predictor variable (Baffigi et al., 2004). In nowcasting GDP, quarterly values of the predictor are employed on the right-hand side and are typically derived from the time aggregation of high-frequency observations of the predictor. To generate nowcasts, the predictors are forecasted using an additional high-frequency model, such as an autoregressive (AR) model. The high-frequency forecasts from this model are aggregated over time to the quarterly frequency and inserted into the bridge equation (Preis & Moat, 2014).

The remainder of the paper is organized as follows: Section 2 presents the literature review. Section 3 provides an overview of the Bhutanese economy. Sections 4 and 5 detail the data preparation and econometric model, respectively. Finally, Sections 6 and 7 discusses the empirical results and conclude the paper with policy recommendations.

2. Literature Review

This section explores into the existing body of research on incorporating high-frequency data into economic forecasting models. The focus is on methodologies that bridge the gap between high-frequency indicators and lower-frequency target variables, particularly GDP growth.

Clements and Galvao (2008) play an important role in this field by proposing a methodology that integrates mixed frequency data into forecasting models. They discuss the construction of bridge equations that link high-frequency indicators to the target variable of US output growth. These bridge equations serve as a mechanism for incorporating timely information from high-frequency data sources into the forecasting process. The authors provide empirical evidence of the effectiveness of their approach by conducting forecasting exercises using real-time data. The forecasting performance of models that incorporate mixed frequency data with those that rely solely on low-frequency data, they demonstrate the potential gains in forecast accuracy achieved through the inclusion of timely information. By highlighting the benefits of utilizing a broader set of data sources, the authors underscore the importance of adapting forecasting methodologies to capitalize on the increasing availability of high-frequency data in today's digital age.

Similarly, Baffigi, Golinelli, and Parigi in 2004, in their paper titled '*Bridge Models to Forecast the Euro Area GDP'*, introduces the concept of bridge models, which serve as a link between leading indicators and final GDP estimates. Bridge models aim to improve the accuracy of GDP forecasts by incorporating timely and relevant information from high-frequency indicators, such as industrial production, consumer confidence, and business surveys. The authors employ a large dataset of monthly and quarterly indicators to estimate latent factors representing the underlying economic conditions. These latent factors are then used to forecast GDP growth through a dynamic regression model. The empirical analysis evaluates the performance of bridge models in forecasting Euro Area GDP growth over different horizons, ranging from one to four quarters ahead. The results indicate that bridge models outperform traditional time-series models, such as autoregressive integrated moving average (ARIMA), especially in the short term.

Additionally, the study by Foroni, Marcellino, and Schumacher (2015) titled '*Unrestricted Mixed Data Sampling (MIDAS): MIDAS Regressions with Unrestricted Lag Polynomials'* introduces a novel approach called Unrestricted Mixed Data Sampling (MIDAS), which relaxes the constraint on lag polynomials imposed by the traditional MIDAS framework. The study demonstrates the effectiveness of the MIDAS approach in capturing complex dynamic relationships between variables with different sampling frequencies. With the lag polynomials, the proposed methodology enables more flexible modelling of lag structures, potentially improving forecast accuracy and parameter estimation.

Underlying the above models is the technique which supports interpolation with large information and data sets for economic analysis. Angelini, Henry, and Marcellino (2006), addresses the critical issue of interpolation by identifying techniques used to estimate unknown values within the range of a discrete set of known data points, particularly relevant with time series data that may be incomplete or unevenly spaced. Through leveraging a large information set and integrating dynamic models with interpolation techniques, the authors provide a robust framework for improving the accuracy and reliability of interpolations. This work not only addresses the limitations of traditional methods but also opens new avenues for research and application in econometrics.

On the contrary, Marcellino (1999), explores the implications of temporal aggregation in empirical economic analysis. Temporal aggregation refers to the practice of summarizing high-frequency data into lower-frequency intervals, such as converting monthly data into quarterly or annual data. Marcellino investigates how temporal aggregation affects the estimated parameters of econometric models suggesting that aggregation can lead to biases in parameter estimates, potentially leading to incorrect inferences about economic relationships. The author highlights the loss of information as high-frequency data often contain valuable information about short-term fluctuations and dynamic relationships that may be obscured or lost when data are aggregated. As a result, the author's findings suggest that aggregation can degrade the performance of forecasting models, particularly those designed to capture high-frequency dynamics, thus suggests methods such as disaggregation and mixed-frequency models, which aim to retain high-frequency information while working with aggregated data (Di Fonzo, 1994).

3. Bhutan's Economy

Before the pandemic, Bhutan had made significant progress in increasing per capita income and reducing poverty, qualifying for graduation from the Least Developed Country (LDC) status in 2023 (Ministry of Finance, 2023). However, the pandemic severely impacted the economy, leading to a contraction in real GDP for two consecutive fiscal years, particularly affecting sectors dependent on physical interaction and external markets (Department of Macro-Fiscal and Development Finance, 2022). Despite these challenges, extensive policy measures and a successful vaccination campaign helped mitigate the negative effects on individuals and their livelihoods (Royal Monetary Authority of Bhutan, 2021).

However, uncertainty regarding the economic outlook remains high, with risks predominantly skewed to the downside. External threats include the potential for a deeper global economic downturn, a slowdown in India, future pandemic waves, heightened geopolitical tensions, and a slow recovery in tourism (Ministry of Finance, 2023). Domestically, risks stem from pandemic-related uncertainties, increased financial sector strains due to limited fiscal capacity, and delays in hydropower projects, all of which could affect growth, external reserves, and debt dynamics (Ministry of Finance, 2023).

From the demand side, consumption accounts for the largest portion of real GDP, making up 70 percent in 2023, with private consumption comprising over 50 percent of total consumption (National Statistics Bureau, 2023). Historically, real GDP growth has been largely driven by consumption and investments, both of which were severely affected by the pandemic. Although their contributions decreased markedly at the start of the COVID-19 pandemic in 2020, consumption rebounded as the primary driver of recovery in 2021 (Ministry of Finance, 2020).

Figure 1 GDP Growth and Contributions

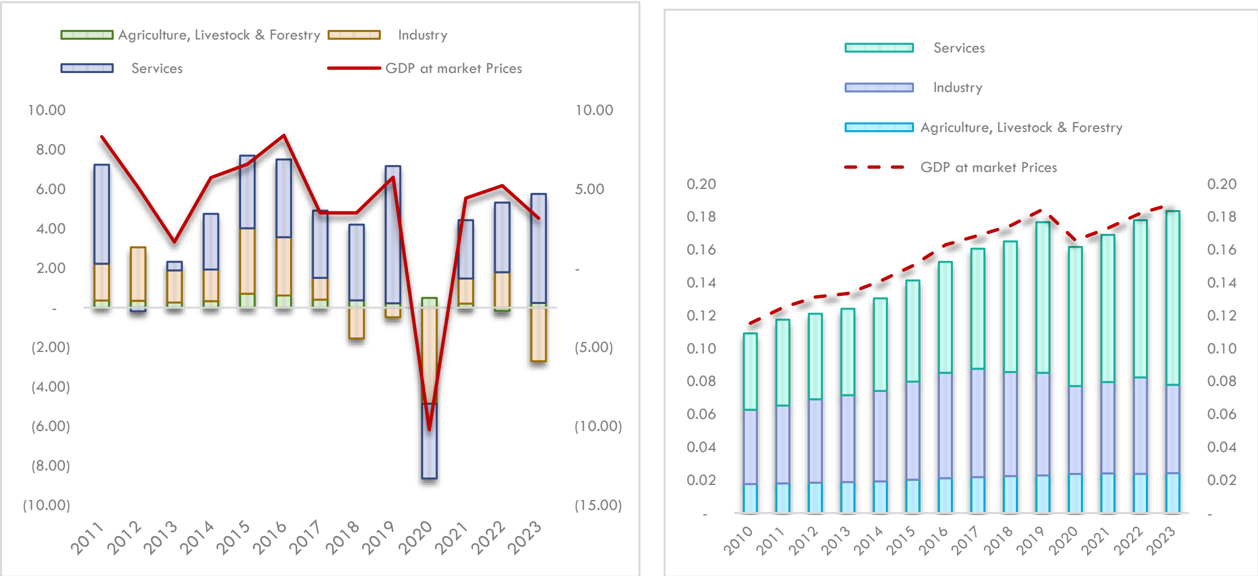
Bhutan: Real Gross Domestic Product: Expenditure *(2010 – 2023, in millions Nu.)*

Source: Author's Calculation

The service and industry sectors play a dominant role in real GDP, collectively accounting for almost 80 percent of the gross value added (GVA), with an equal distribution between them. These sectors have traditionally been key drivers of economic growth in Bhutan, especially before the COVID-19 pandemic. However, the outbreak of the COVID-19 pandemic has had a notable impact, particularly on the service sector, which includes contact-intensive services. As a result, the contribution of the services sector to economic activity has decreased during the pandemic.

Figure 2: Sectoral Composition of GDP

Bhutan: Real Gross Domestic Product: Economic Sectors (2011 – 2023, in millions Nu.)



Source: Author's Calculation

Based on the official macroeconomic projections for the third quarter, the Ministry of Finance (2024) expects Bhutan's economy to expand by 3.16 percent in 2023 and by 5.7 percent in 2024. This forecast hinges on the effective implementation of the 13th Five Year Plan, addressing supply chain disruptions, and the gradual return to normal economic activities throughout 2024.

In the medium term, the Ministry expects the potential growth to recover in 2024-25, with the normalization of economic activity and improvement in the labour market conditions. Investments and reforms under the new five-year plan would be critical in limiting the economic scarring, compensating for slower capital accumulation during the pandemic, and boosting productivity. Nonetheless, the slow recovery in contact-intensive sectors and labour market dislocation could lead to some hysteresis.

4. Data Preparation

Economic conditions are routinely evaluated by policy makers and economic analysts in Bhutan. However, they face challenges due unavailability of high frequency GDP data. As a result, there is a dire need for more timely data to accurately evaluate the current business environment and facilitate informed decision-making.

Hence, to address the challenge posed by data gaps, various studies indicate that leading economic indicators consistently offer early signals of shifts in economic activity (Clements & Galvao, 2009). Consequently, extensive research has been devoted in identifying the most effective indicators. Burns and Mitchell (1938 and 1946) devoted in obtaining an empirical characterization of the business cycle by defining business cycle to be a type of fluctuation found in aggregate economic activity. Their work drew upon a comprehensive understanding of both historical trends and theoretical frameworks related to business cycles, supported by a vast amount of empirical data. As a result of their research, they introduced the concepts of leading, coincident, and lagging indicators, as well as composite indices, to track and analyse economic cycles (Mitchell and Burns, 1938). For this paper, we will focus specifically on leading indicators, which are predictive of future changes in economic activity. Our aim is to identify indicators that closely track movements in GDP and have a strong correlation with GDP growth (Auerbach, 1982).

Leading indicators forecast changes in the economy by signalling future economic activity. They are effective because they often represent decisions or commitments to economic activity in the months ahead (Zheng & Rossiter, 2006). Hence, this study has opted to examine and analyse high-frequency indicators such as imports, investments, electricity generation, manufacturing output, and overall consumption in order to forecast GDP, a methodology closely associated with nowcasting.

Our primary objective is to extend Bhutan's real GDP data to 2024Q1 using higher frequency (i.e, monthly) data of the leading indicators. This will involve the use of three-monthly series, all of which have been recently updated according to the third-quarter macroeconomic framework provided by the Ministry of Finance.

Table 1 Summary Statistics of the Data

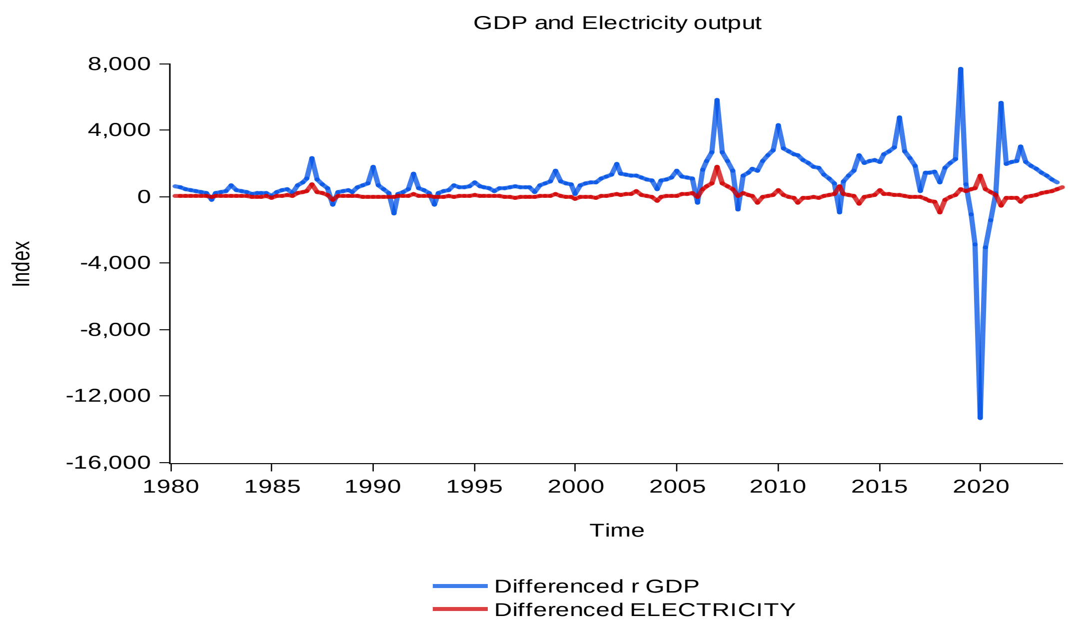
	R_GDP	CONSUMPTION	ELECTRICITY	IMPORTS	INVESTMENT	MANUFACTURING
Mean	80232.61	20129.68	4996.976	16215.08	14257.44	2545.061
Median	58613.16	15304.54	2512.869	11536.25	12003.86	1843.663
Maximum	189396.6	58066.32	12972.1	34767.12	34312.7	6149.399
Minimum	12276.28	2923.799	-41.35312	1325.798	1662.662	19.2379
Std. Dev.	58039.83	15990.28	4133.547	12539.32	10750.3	1974.423
Skewness	0.578361	0.725332	0.413465	0.302068	0.51174	0.422651
Kurtosis	1.850223	2.309527	1.540328	1.380007	1.793821	1.617502
Observations	176	177	177	177	177	177

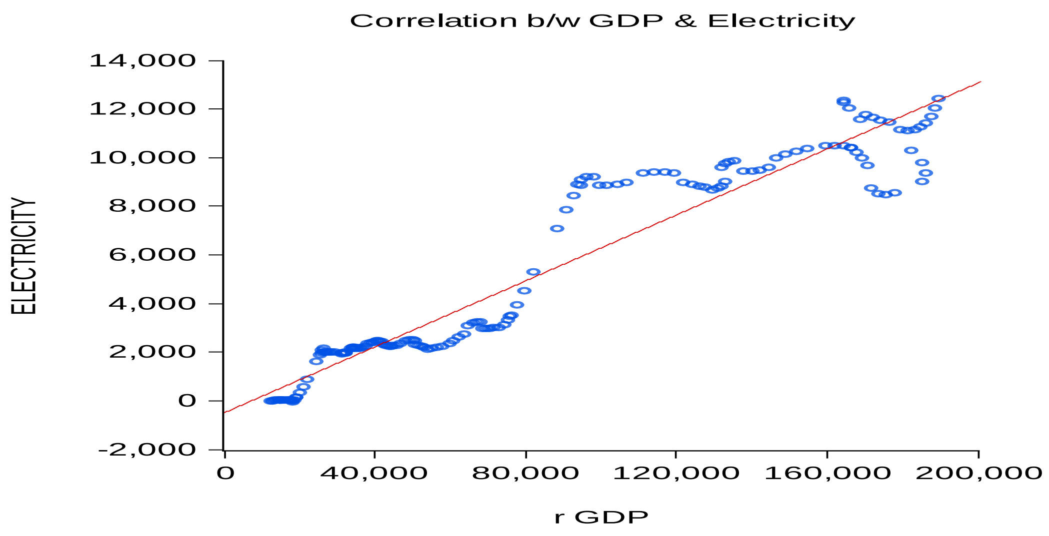
Source: Author's calibration based on MFCTC data

The following variables provides an explanation of the data used in the model.

- **Electricity production, available until 2023M12 (Department of Energy, 2023)**. Over time, electricity has been a consistent driver of industrial sector expansion, maintaining export revenues despite economic turbulence. The resilience of the electricity sector underscores its significant contribution to Bhutan's economy, accounting for over 12 percent of the real GDP in 2023.

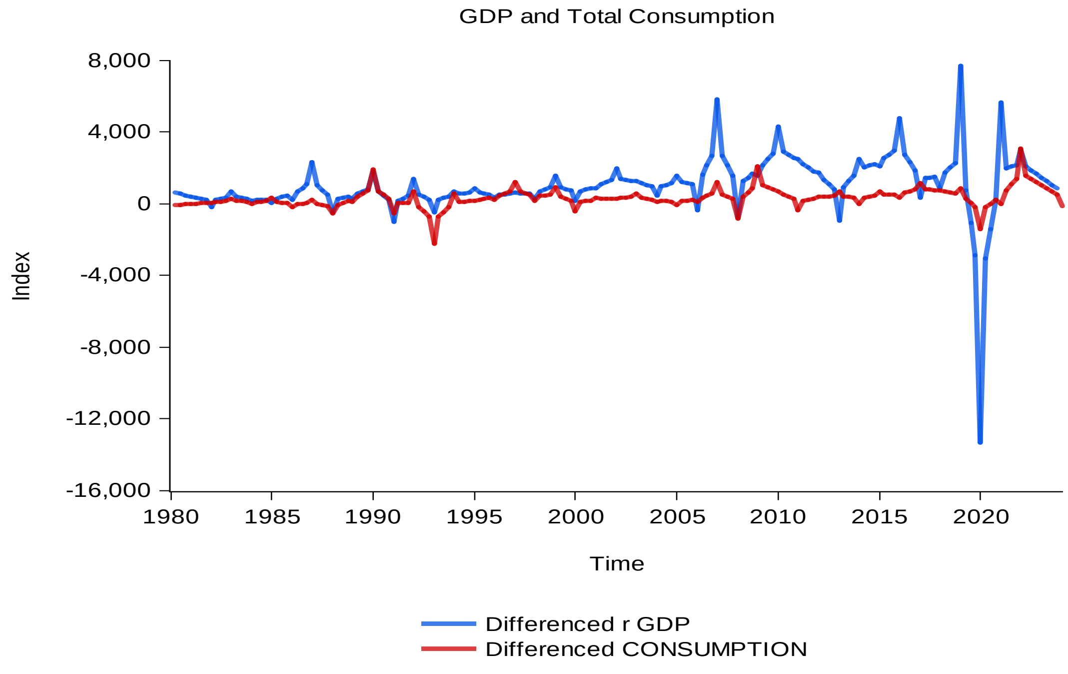
Figure 3 Real GDP growth vis-a-vis Electricity (1980~2023)

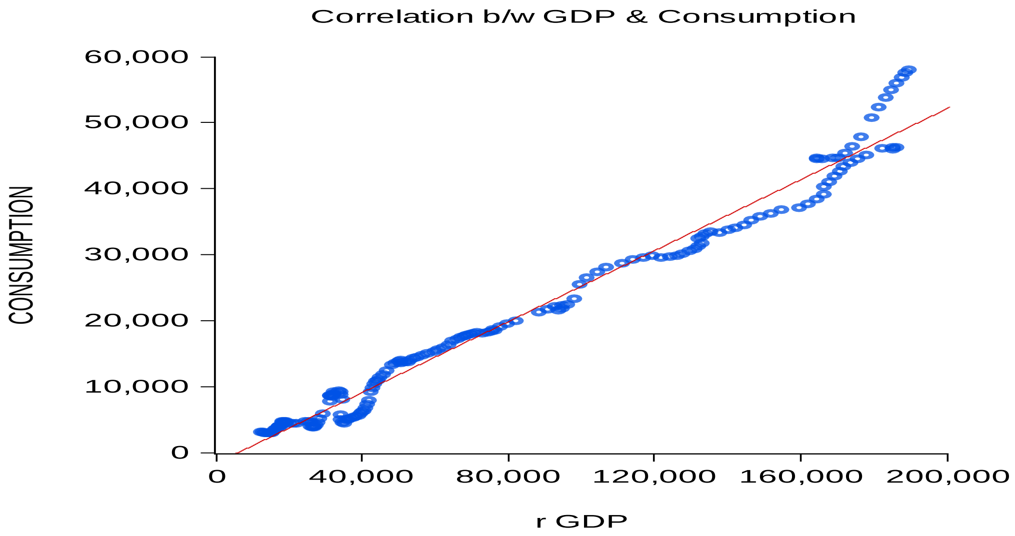




- **Total consumption (Private and public consumption) available until 2023M12 (Ministry of Finance, 2023).** Consumption plays an important role in the economy as it represents consumer demand for goods and services, indicating the importance of aggregate demand. In 2023, total consumption accounted for over 70 percent of Bhutan's real GDP. Therefore, an increase in total consumption has a positive impact on real GDP growth.

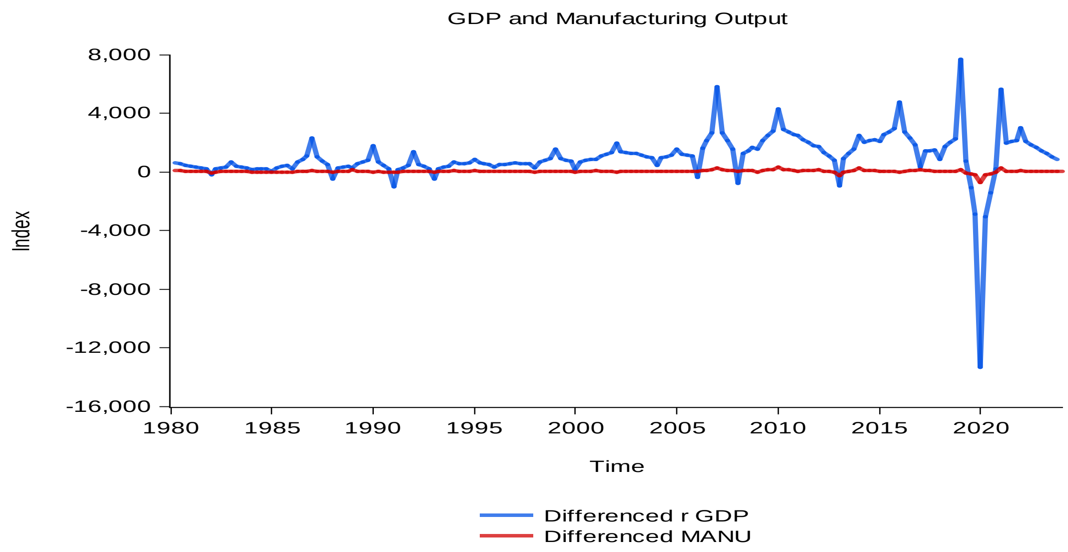
Figure 4 Total Consumption vis-a-vis Real GDP (1980 ~ 2023)

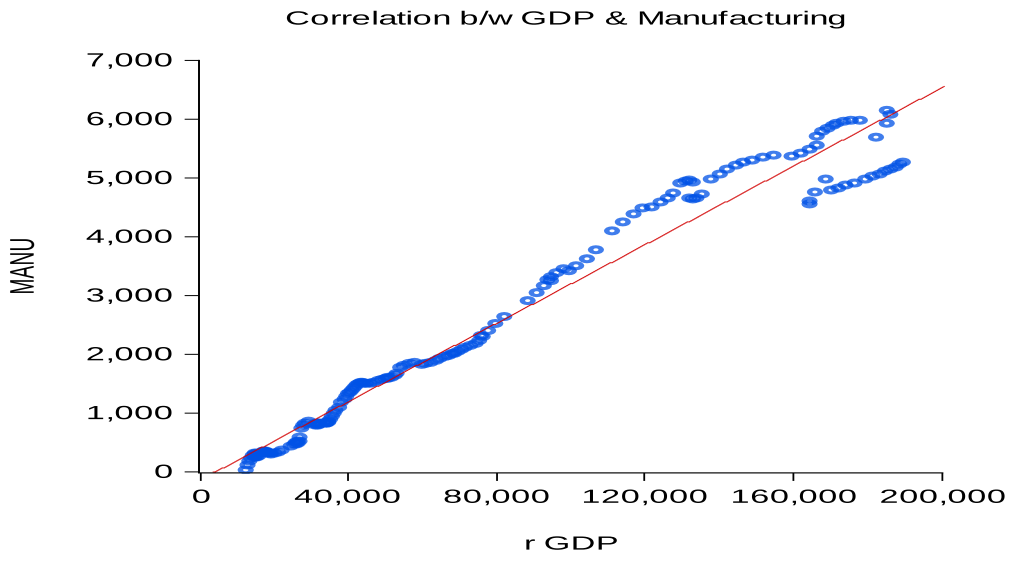




- **Manufacturing Sector output, available until 2023M12 (National Statistics Bureau, 2023).** This data represents the monthly production across different industries in Bhutan. It emphasizes the importance of industry sectors in Bhutan's economic landscape. In 2023, the manufacturing sector contributed 5.5 percent to the country's real GDP and accounted for nearly 20 percent of the industry sector. Overall, the manufacturing sector is crucial for driving economic growth, as it generates output, creates employment opportunities, encourages innovation, and stimulates economic activity across the entire supply chain.

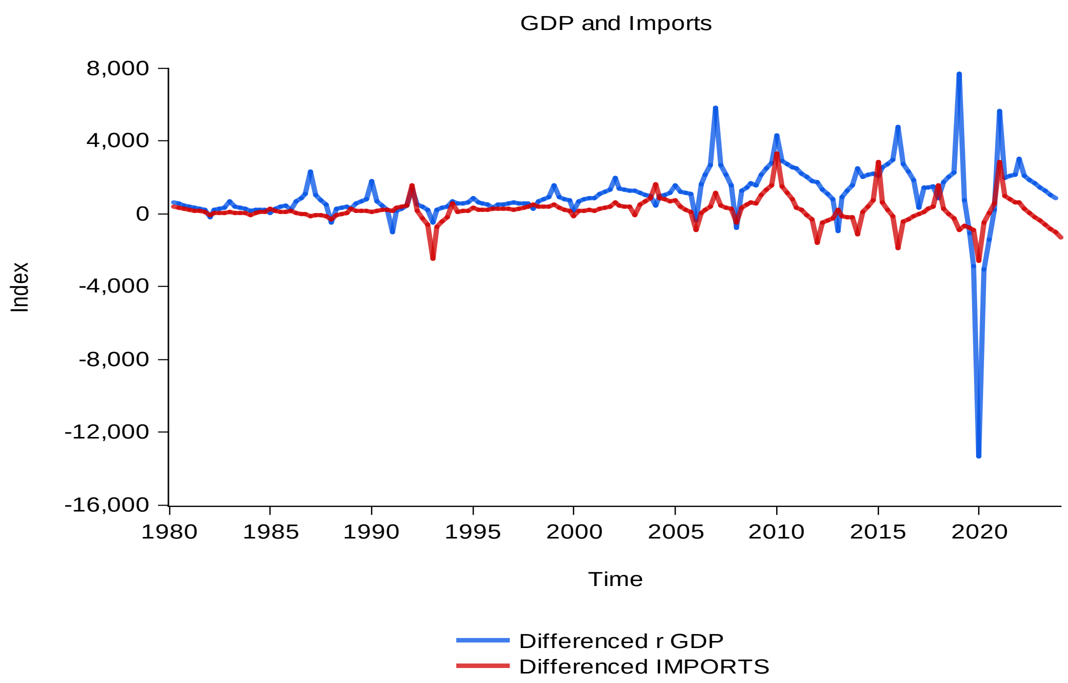
Figure 5. Manufacturing sector vs. Real GDP (1980 ~ 2023)

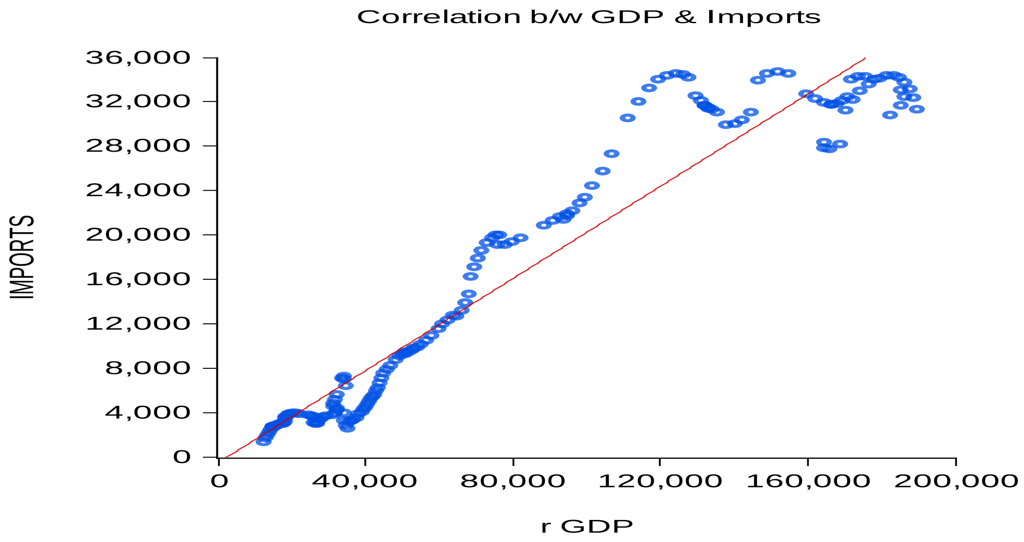




- **Imports, available until 2023M12 (Department of Revenue & Customs, 2023).** Given Bhutan's reliance on imports for essential goods, fluctuations in import volumes offer valuable indicators of economic performance and underlying demand dynamics. Empirical evidence supports the relevance of imports in forecasting Bhutan's GDP, as they typically constitute approximately 50 percent of the total GDP. Therefore, imports are selected as a key explanatory factor in GDP nowcasting models for Bhutan.

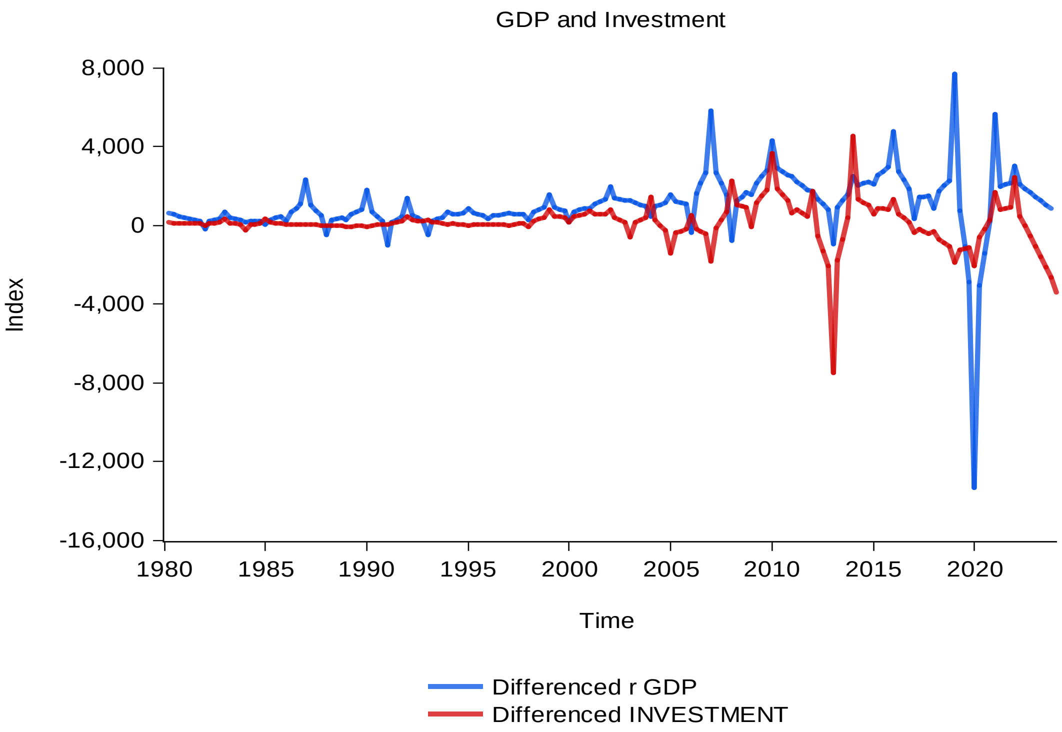
Figure 6. Imports vs. Real GDP (1980 ~ 2023)

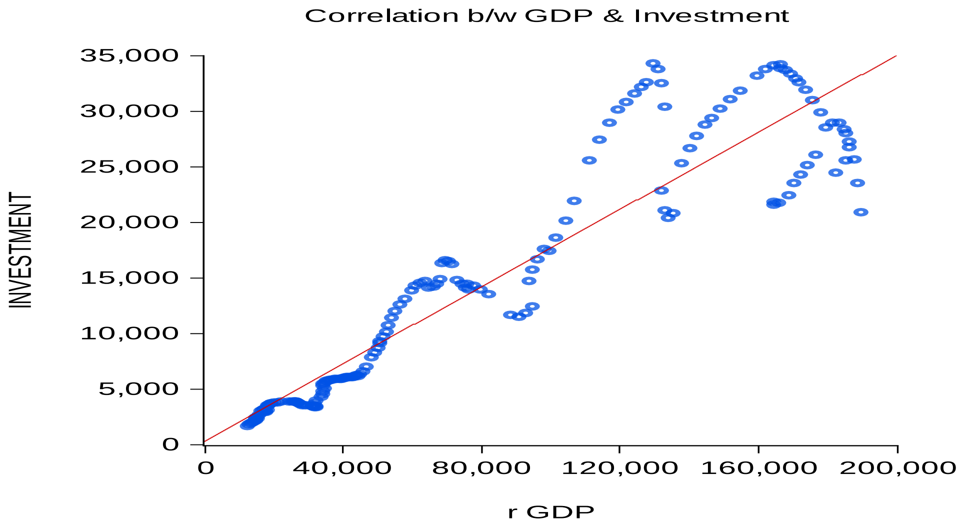




- **Investment, available until 2023M12 (National Statistics Bureau, 2023).** Investment is a critical driver of economic growth and influences the accumulation of stock of capital goods, such as machinery, infrastructure, and technology. As a share of GDP, investment consists of almost 50 percent of overall GDP thereby indicating a strong correlation with GDP.

Figure 7. Investment vs. Real GDP (1980 ~ 2023)





After identifying the leading indicators and their association with GDP, we proceed to convert the frequency of GDP data from a lower frequency to a higher one. Specifically, we employ a Quadratic (Match: Average) conversion method. This technique involves interpolating the low-frequency GDP data to generate high-frequency observations. To achieve this, the method utilizes quadratic polynomials, which are fitted to groups of three neighbouring points from the low-frequency data (Denton, 1971, pp. 99–102). The quadratic polynomial is adjusted so that the average of the high-frequency data points aligns with the observed low-frequency data. Further, the baseline forecasting model for real GDP is determined through an autoregressive distributed lag model for quarterly GDP growth measured using log differences (Giannone, Agrippino, & Modugno, 2013).

5. Econometric Model and Empirical Strategy

5.1 ARIMA selection procedure

Based on the specified exogenous variables, a conventional criterion is employed to select the most suitable ARIMA model for a given dataset. For this study, we use the Akaike Information Criterion (AIC) alongside Mean Square Error (MSE) considering its efficacy in striking a balance between the goodness of fit of models and effectively penalizing models with more parameters. The following highlights the basic formula for these two types of model selection criterion.

Information Criteria: Each of the criteria are based upon the estimated log-likelihood of the fitted model, the number of parameters, and observations in the model. The model with the smallest information criterion is preferred.

Akaike Info Criterion (AIC): $-2\frac{l}{T} + 2k\frac{1}{T}$

where l is the value of the log of the likelihood function, k is the number of parameters estimated using T observations.

Mean Saure Error (MSE) Evaluation: this is also called in-sample forecast evaluation, in which each model is estimated using a sub-sample (i.e., first 80%-90% of the data) and forecasted over the remaining data (i.e., 10%-20%). Then the MSE is calculated according to

Mean Square Error (MSE) $= \frac{l}{h}\sum_{t=T-h}^{T}(y_t - \hat{y}_t)^2$

where h is the number of periods in the forecast sub-sample, y_t is the actual data, $\hat{y}_t$ is the forecast at time t, and T is the number of observations in the sample. The model with the smallest MSE is selected.

5.1.1 Adjusted Stepwise ARIMA variable selection procedure.

Stepwise model selection techniques, commonly used in regression analysis, are employed to determine the most suitable baseline forecasting or nowcasting model. These methods involve the iterative addition or removal of variables based on their statistical significance. The process typically begins with either backward elimination from a comprehensive model or forward inclusion from a simpler model.

In forward selection, variables are sequentially added to the model based on their level of statistical significance. This approach ensures that only statistically significant variables are included, while removing those that are not. Conversely, backward selection begins with all candidate variables included in the model and then eliminates individual variables if they are found to be insignificant.

Overall, stepwise model selection procedures help identify the most appropriate model by iteratively refining the set of included variables based on their statistical significance (Chowdhury and Turin 2020). Therefore, we decide whether a variable (X_t) is a suitable candidate based on three criteria:

- Condition 1: The X_t decreases the Akaike Information Criteria (AIC) value.
- Condition 2: The coefficient sign of X_t matches economic priors.
- Condition 3: X_t is statistically significant at the 5% confidence level.

To illustrate the proposed procedure, we select variables to nowcast Bhutan's real GDP(Y_t) from the following pre-selected, exogenous indicators shown in Table 1. The pre-selected data include macroeconomic variables explained in section 4. The data has been obtained from macroeconomic framework of Bhutan (Ministry of Finance, 2023).

Table 2 Pre-selected data to Nowcast Bhutan's Real GDP

Series Name	**Description**	**Start**	**End**	**Source**
electricity_hydro	Bhutan: Hydropower production	Jan-1980	Dec-2023	DHPS
imports	Bhutan: Total Imports	Jan-1980	Dec-2023	DRC
total_consumption	Bhutan: Public/Private consumption	Jan-1980	Dec-2023	MoF/NSB
manufacturing_inds	Bhutan: Industrial Production	Jan-1980	Dec-2023	NSB
investment_gfcf	Bhutan: Gross fixed capital formation	Jan-1980	Dec-2023	MoF/NSB
Wholesale_retail	Bhutan: Wholesale and Retail trade	Jan-1980	Dec-2023	MoF/NSB

Source: Author's calibration

We initiate the exogenous selection process by examining the first indicator, DLOG(ELECTRICITY_HYDRO), and then iterate the process for the other variables. Table 2 provides a comprehensive overview of each indicator's performance and how they satisfy the initial two acceptance criteria. Upon completing step 2, we find that five indicators fulfill bothconditions: DLOG(ELECTRICITY_HYDRO), DLOG(IMPORTS), DLOG(TOTAL_CONSUMPTION), DLOG(MANUFACTURING_INDS), and DLOG(INVESTMENT_GFCF), enabling us to proceed to step 3.

Table 3 provides a comprehensive overview of the statistics associated with each variable selection. Areas shaded in grey signify that the indicator meets the specified criterion. For instance, DLOG(ELECTRICITY_HYDRO), DLOG(IMPORTS), DLOG(TOTAL_CONSUMPTION), DLOG(MANUFACTURING_INDS), and DLOG(INVESTMENT_GFCF) demonstrates a decrease in the AIC value and exhibits statistical significance. The final column summarizes the number of conditions fulfilled by each variable, leading to the retention of only those variables that meet both the criteria.

Table 3 Automatic ARIMA Stepwise Variable Selection – Steps 1 and 2 Result

Selected	Iterations	Variable (X) Added	*Condition 1*		*Condition 2*		*Condition 3*		# of Conditions Met
			AIC Value		*Coefficient*		*P-Value*		
			AR(3) MA(3)	*AR(3) MA(6)*	*AR(3) MA(3)*	*AR(3) MA(6)*	*AR(3) MA(3)*	*AR(3) MA(6)*	
√	1	dlog(electricity_hydro)	12.341	12.04	(0.732) (-0.116)	(0.431) (0.974)	(0.0000) (0.0734)	(0.0000) (0.0000)	2
√	2	dlog(imports)	14.385	14.013	(0.683) (-0.104)	(0.410) (0.972)	(0.0000) (0.1378)	(0.0000) (0.0000)	2
√	3	dlog(total_consumption)	13.7	13.37	(0.814) (-0.163)	(0.5) (0.97)	(0.0000) (0.0050)	(0.0000) (0.0000)	2
√	4	dlog(manufacturing_inds)	10.321	9.827	(0.685) (-0.121)	(0.421) (0.994)	(0.0000) (0.0832)	(0.0000) (0.0000)	2
√	5	dlog(investment_gfcf)	15.179	14.813	(0.691) (-0.100)	(0.433) (1.019)	(0.0000) (0.1553)	(0.0000) (0.0000)	2
×	6	dlog(whlsale_retail)	10.109	9.657	(0.77) (-0.166)	(0.488) (1.00)	(0.0000) (0.0000)	(0.0000) (0.9067)	1

With the five variables selected from Steps 1 and 2, we can proceed with Step 3, which brings the selected variables to the automatic ARIMA procedure to assess **Condition 3** (statistical significance) and reassess **Condition 2** (coefficient sign consistent with economic priors). The variables, along with the automatically selected ARIMA terms, are then used to formulate the baseline nowcasting model based on the fulfillment of the conditions.

5.2 Bridge Estimation

One of the econometric approaches to forecast in the presence of mixed-frequency data is a bridge equation approach. A bridge model is a linear regression model that links high frequency variables to low frequency ones (Baffigi et al, 2004). The inclusion of specific RHS variables/indicators is not based on causal relations, but on the statistical fact that they contain timely updated information. First, monthly indicators are forecast over the remainder of the quarter, usually based on univariate time series models, and then aggregated to obtain their corresponding quarterly values. Second, the aggregated (low frequency) values are used as regressors in the bridge equation which allows to obtain forecasts of the low frequency target variable.

To perform nowcasting of quarterly GDP, the high-frequency indicators (such as monthly data) are first transformed to match the lower, target frequency (such as quarterly data) by aggregating the observations within each quarter, typically through summing or averaging.

Subsequently, the Bridge model is estimated using ordinary least squares (OLS). Unlike a more structural model, the selection of variables or indicators in the Bridge model is not based on causal relationships but on an assumption or prior belief that they contain timely and informative data regarding the future direction of the dependent variable, such as real GDP. The Bridge model's simplicity and transparency have led numerous policy institutions to utilize it for guiding policy decisions (Ingenito & Trehan, 1996; Baffigia, Golinellib, & Parigia, 2004; Foroni & Marcellino, 2013).

The bridge model can be represented as

$$y_{tq} = \alpha + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \sum_{i=1}^{j} \beta_i x_{it_q} + u_{t_q}$$

where β_i is the coefficient of the exogenous regressor, t_q = 1., T indicates time in quarters, x_i is a high-frequency indicator, and u_{t_q} is an i.i.d. error term. Moreover, $\sum_{i=1}^{p} \varphi_i Y_{t-i}$ is the autoregressive (AR) term of order p(i.e., AR(p)) and $\sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$ is the moving average (MA) of q (i.e., MA (q)).

5.3 Mixed Data Sampling Method (MIDAS)

The MIDAs model are tightly parameterized reduced form regressions with variables sampled at different frequencies (Ghysels et al 2004). MIDAS models have been employed and have demonstrated potential in forecasting contexts (Kuzin et al., 2013) as well as in structural analysis (Ferrara and Guérin, 2018). MIDAS models are suitable to our context, where monthly variables are used to forecast quarterly GDP growth. Unlike bridge equation models, which depend on auxiliary regressions to forecast explanatory variables, MIDAS models serve as a direct forecasting tool. They directly estimate the current quarter using a lag structure that corresponds to ragged edge data. The response of the dependent variable (i.e., GDP) to the high frequency explanatory variable (electricity, manufacturing, consumption, imports, investment) is modelled using distributed lag polynomials with coefficients depending on a small number of parameters, to prevent parameter proliferation when frequency mismatch is large. The following provides the MIDAS model designed for this purpose:

$$y_t = \beta_0 + \sum_{j=0}^{k} \beta_j B\left(L^{\frac{1}{m}}; \theta\right) x_{t-j/m} + \epsilon_t$$

where y_t represents the low frequency dependent variable, $x_{t-j/m}$ indicates the high frequency variables, m is the frequency ratio and $B(L^{\frac{1}{m}};\ \theta)$ is the lag polynomial applied to the high frequency variable, parameterized by θ.

In the standard MIDAS literature, functional lag polynomials are employed to avoid parameter proliferation in the case of long high-frequency lags (Andreou et al., 2010). The base model allows for up to 12 lags (including the 0 lag) of each split-sampled high frequency indicator, with the optimal number chosen using Akaike Information Criterion.

6. Empirical Results

In this section, our objective is to nowcast the current quarter's GDP and forecast the GDP for the following quarter. For example, to nowcast the GDP for the first quarter of 2024, we need monthly data for high-frequency indicators (HFIs) up to December 2023. Table 4 below summarizes the variables, their sources, data frequency, and starting dates.

Table 4 Candidate Indicators

Indicator	Unit	Frequency	Source	Starting Date	End Date
Population	persons	Annual	NSB	1980	2023
GDP (nominal)	in millions ngultrum	Annual	NSB	1980	2023
Government fiscal deficit	in millions ngultrum	Quarterly/Annual	MoF	1980Q1	2023Q4
Total expenditure	in millions ngultrum	Monthly	MoF	1980M1	2023M12
Current expenditure (Consumption)	in millions ngultrum	Monthly	MoF	1980M1	2023M12
Capital expenditure	in millions ngultrum	Monthly	MoF	1980M1	2023M12
Primary balance	in millions ngultrum	Quarterly/Annual	MoF	1980Q1	2023Q4
Total domestic revenue	in millions ngultrum	Monthly	MoF	1980M1	2023M12
M2	in millions ngultrum	Monthly	RMA	1980M1	2023M12
Private credit	in millions ngultrum	Monthly	RMA	1980M1	2023M12
Rupee reserves	in million INR	Monthly	RMA	1980M1	2023M12
Foreign reserves	in million USD	Monthly	RMA	1980M1	2023M12
Total reserves	in million USD	Monthly	RMA	1980M1	2023M12
Total consumption	in millions ngultrum	Monthly	MoF	1980M1	2023M12
Investment	in millions ngultrum	Monthly	MoF	1980M1	2023M12
Tax revenue	in millions ngultrum	Monthly	MoF	1980M1	2023M12
Direct tax revenue	in millions ngultrum	Monthly	MoF	1980M1	2023M12
Indirect tax revenue	in millions ngultrum	Monthly	MoF	1980M1	2023M12
Non-tax revenue	in millions ngultrum	Monthly	MoF	1980M1	2023M12
Hydro-revenue	in millions ngultrum	Monthly	MoF/DHPS	1980M1	2023M12
Trade balance	in millions ngultrum	Monthly	DRC/NSB	1980M1	2023M12
Imports	in millions ngultrum	Monthly	DRC/NSB	1980M1	2023M12
Export	in millions ngultrum	Monthly	DRC/NSB	1980M1	2023M12
Current account balance	in millions ngultrum	Monthly	RMA/MoF	1980M1	2023M12
Real GDP per capita growth rate	%	Annual	NSB	1980	2023
Real GDP per capita	in millions ngultrum	Annual	NSB	1980	2023
GDP	in millions ngultrum	Annual	NSB	1980	2023
Inflation rate	%	Annual	NSB	1980	2023
Gross Fixed Capital Formation/Investment	in millions ngultrum	Monthly	MoF/NSB	1980M1	2023M12
Hydropower/Electricity	in millions ngultrum	Monthly	MoF/DHPS	1980M1	2023M12
Manufacturing Sector	in millions ngultrum	Monthly	MoF/NSB	1980M1	2023M12
Wholesale Retail Trade	in millions ngultrum	Monthly	DRC/NSB	1980M1	2023M12
Private Consumption	in millions ngultrum	Monthly	MoF/NSB	1980M1	2023M12

Beginning with the 33 indicators detailed in the table, the ARIMA indicator selection procedure narrowed it down to five variables for the baseline model, which includes AR(3) MA(3) terms (see Table 3). The selected indicators are:

i) electricity_hydro
ii) Imports
iii) total_consumption
iv) manufacturing_inds
v) investment_gfc

The selection procedure ensures that the chosen indicators are statistically significant at the 5% confidence level, indicating a high degree of reliability in their contribution to the model. Additionally, the estimated coefficients for these indicators not only achieve statistical significance but also align with theoretical expectations by displaying the correct sign. This consistency with theoretical predictions reinforces the validity of the model, as it suggests that the indicators are influencing the dependent variable in the anticipated direction.

The AR(3) MA(6) model has been selected based on significant statistics and model fit criteria based on Akaike info criterion. The model effectively captures the autocorrelation structure up to lag 6, as indicated by the significant Q-statistics. Each AR and MA term in the model is statistically significant at 5%, indicating their importance in explaining the variability in the time series data. Hence, the AR(3) MA(6) ARIMA model turns out to be a robust model for baseline nowcasting, addressing the significant autocorrelations identified in the initial correlogram (Box et al., 2015).

Table 5 ARIMA Model for Total Consumption based on Monthly data

Dependent Variable: D(TOTAL_CONSUMPTION)

Method: ARMA Conditional Least Squares

Sample (adjusted): 1980M05 2023M12

Included observations: 524 after adjustments

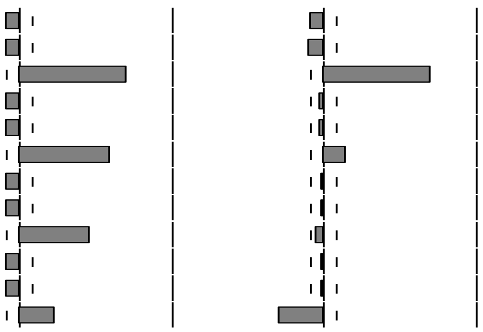
Convergence achieved after 11 iterations

MA Backcast: 1979M11 1980M04

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	105.2684	33.64284	3.129000	0.0019
AR(3)	0.504325	0.037872	13.31648	0.0000
MA(6)	0.976039	0.005566	175.3617	0.0000

R-squared	0.679809	Mean dependent var	104.9401
Adjusted R-squared	0.678580	S.D. dependent var	341.1481
S.E. of regression	193.4103	Akaike info criterion	13.37321
Sum squared resid	19489331	Schwarz criterion	13.39761
Log likelihood	-3500.782	Hannan-Quinn criter.	13.38277
F-statistic	553.0764	Durbin-Watson stat	2.038339
Prob(F-statistic)	0.000000		

Autocorrelation | Partial Correlation



	AC	PAC	Q-Stat	Prob
1	-0.093	-0.093	4.6332	0.031
2	-0.093	-0.103	9.2640	0.010
3	0.735	0.730	298.31	0.000
4	-0.094	-0.017	303.02	0.000
5	-0.094	-0.017	307.71	0.000
6	0.611	0.151	508.50	0.000
7	-0.093	-0.011	513.21	0.000
8	-0.093	-0.011	517.89	0.000
9	0.469	-0.056	637.02	0.000
10	-0.093	-0.012	641.69	0.000
11	-0.092	-0.012	646.33	0.000
12	0.234	-0.309	676.20	0.000

Source: Author's calculation

Table 6 ARIMA Model for Electricity based on Monthly data

Dependent Variable: D(ELECTRICITY)

Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)

Sample (adjusted): 1980M05 2023M12

Included observations: 524 after adjustments

Convergence achieved after 20 iterations

MA Backcast: 1979M11 1980M04

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	25.79193	15.06541	1.711997	0.0875
AR(3)	0.431726	0.039751	10.86080	0.0000
MA(6)	0.974003	0.005872	165.8730	0.0000

R-squared	0.588418	Mean dependent var	23.70842
Adjusted R-squared	0.586838	S.D. dependent var	154.5636
S.E. of regression	99.34989	Akaike info criterion	12.04088
Sum squared resid	5142479.	Schwarz criterion	12.06528
Log likelihood	-3151.711	Hannan-Quinn criter.	12.05044
F-statistic	372.4235	Durbin-Watson stat	2.010939
Prob(F-statistic)	0.000000		

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.024	-0.024	0.3152	0.574
		2	-0.024	-0.025	0.6302	0.730
		3	0.661	0.660	234.18	0.000
		4	-0.024	-0.004	234.49	0.000
		5	-0.024	-0.004	234.79	0.000
		6	0.498	0.108	368.00	0.000
		7	-0.023	-0.003	368.29	0.000
		8	-0.023	-0.003	368.58	0.000
		9	0.312	-0.094	421.43	0.000
		10	-0.023	-0.005	421.71	0.000
		11	-0.023	-0.005	421.99	0.000
		12	0.038	-0.305	422.79	0.000

Source: Author’s calculation

Table 7 ARIMA Model for Imports based on Monthly data

Dependent Variable: D(IMPORTS)

Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)

Sample (adjusted): 1980M05 2023M12

Included observations: 524 after adjustments

Convergence achieved after 20 iterations

MA Backcast: 1979M11 1980M04

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	49.85189	38.94066	1.280202	0.2010
AR(3)	0.410702	0.040204	10.21543	0.0000
MA(6)	0.972571	0.006408	151.7712	0.0000

R-squared	0.571832	Mean dependent var	56.52153
Adjusted R-squared	0.570188	S.D. dependent var	406.4045
S.E. of regression	266.4390	Akaike info criterion	14.01388
Sum squared resid	36985652	Schwarz criterion	14.03827
Log likelihood	-3668.636	Hannan-Quinn criter.	14.02343
F-statistic	347.9056	Durbin-Watson stat	2.006507
Prob(F-statistic)	0.000000		

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.018	-0.018	0.1730	0.677
		2	-0.018	-0.018	0.3476	0.840
		3	0.612	0.612	200.75	0.000
		4	-0.018	-0.005	200.93	0.000
		5	-0.019	-0.005	201.12	0.000
		6	0.433	0.093	301.80	0.000
		7	-0.019	-0.004	301.99	0.000
		8	-0.019	-0.004	302.19	0.000
		9	0.234	-0.102	331.84	0.000
		10	-0.019	-0.005	332.05	0.000
		11	-0.020	-0.005	332.25	0.000
		12	-0.088	-0.363	336.46	0.000

Source: Author's calculation

Table 8 ARIMA Model for Investment based on Monthly data

Dependent Variable: D(INVESTMENT)

Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)

Sample (adjusted): 1980M05 2023M12

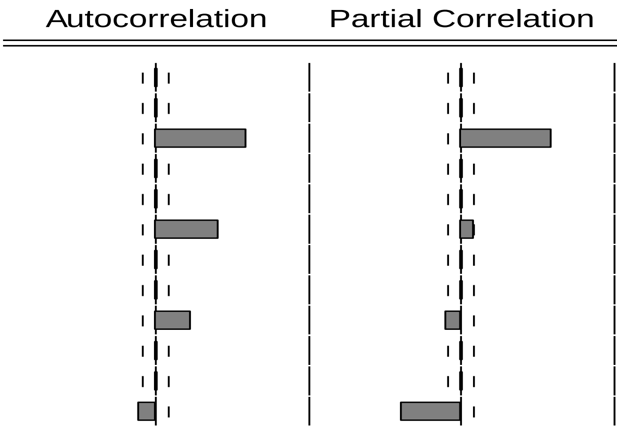
Included observations: 524 after adjustments

Convergence achieved after 13 iterations

MA Backcast: OFF (Roots of MA process too large)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	29.97617	19.99811	1.498950	0.1345
AR(3)	0.433602	0.040295	10.76078	0.0000
MA(6)	1.019834	0.004067	250.7486	0.0000

R-squared	0.572334	Mean dependent var	36.47818
Adjusted R-squared	0.570692	S.D. dependent var	606.5387
S.E. of regression	397.4137	Akaike info criterion	14.81354
Sum squared resid	82285535	Schwarz criterion	14.83794
Log likelihood	-3878.148	Hannan-Quinn criter.	14.82310
F-statistic	348.6202	Durbin-Watson stat	2.001686
Prob(F-statistic)	0.000000		



	AC	PAC	Q-Stat	Prob
1	-0.001	-0.001	0.0005	0.981
2	-0.001	-0.001	0.0010	1.000
3	0.615	0.615	202.13	0.000
4	-0.002	-0.002	202.13	0.000
5	-0.002	-0.002	202.13	0.000
6	0.430	0.085	301.82	0.000
7	-0.003	-0.001	301.82	0.000
8	-0.002	-0.001	301.83	0.000
9	0.231	-0.103	330.62	0.000
10	-0.003	-0.001	330.63	0.000
11	-0.003	-0.001	330.63	0.000
12	-0.111	-0.394	337.35	0.000

Source: Author's calculation

Table 9 ARIMA Model for Manufacturing based on Monthly data

Dependent Variable: D(MANUFACTURING)

Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)

Sample (adjusted): 1980M05 2023M12

Included observations: 524 after adjustments

Convergence achieved after 33 iterations

MA Backcast: 1979M11 1980M04

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9.384636	4.459374	2.104474	0.0358
AR(3)	0.421670	0.039742	10.61022	0.0000
MA(6)	0.994511	0.005236	189.9218	0.0000

R-squared	0.619694	Mean dependent var	9.829995
Adjusted R-squared	0.618234	S.D. dependent var	53.17731
S.E. of regression	32.85679	Akaike info criterion	9.827903
Sum squared resid	562455.4	Schwarz criterion	9.852301
Log likelihood	-2571.911	Hannan-Quinn criter.	9.837457
F-statistic	424.4741	Durbin-Watson stat	2.016718
Prob(F-statistic)	0.000000		

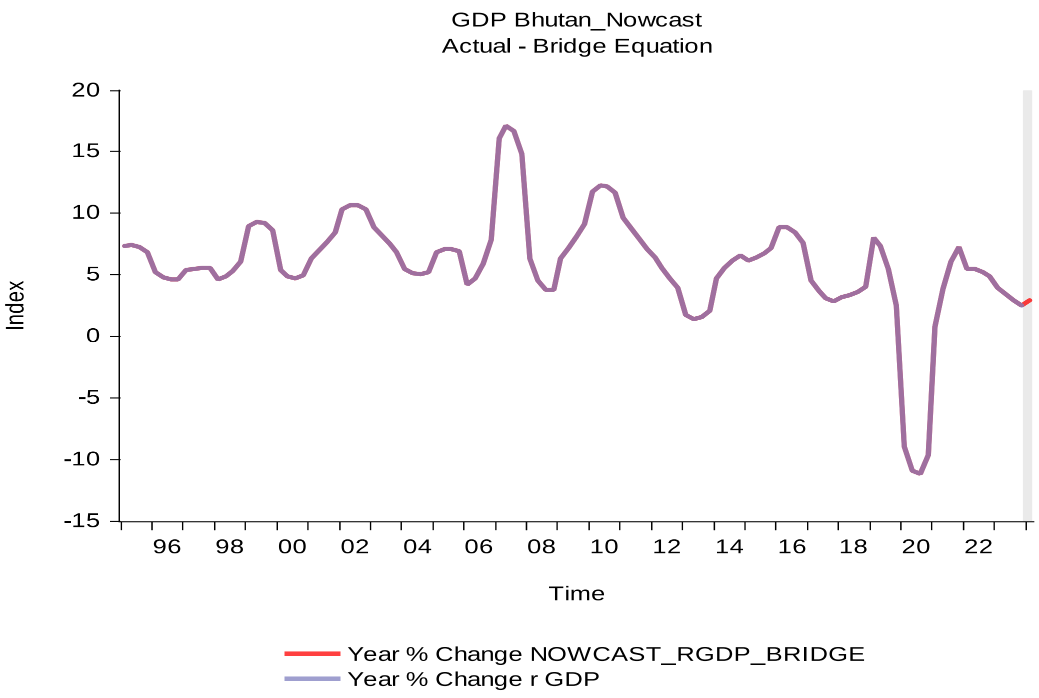
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.035	-0.035	0.6606	0.416
		2	-0.035	-0.037	1.3234	0.516
		3	0.609	0.608	199.46	0.000
		4	-0.035	-0.008	200.10	0.000
		5	-0.035	-0.008	200.75	0.000
		6	0.439	0.108	304.24	0.000
		7	-0.034	-0.006	304.87	0.000
		8	-0.034	-0.007	305.50	0.000
		9	0.253	-0.082	340.21	0.000
		10	-0.034	-0.008	340.83	0.000
		11	-0.034	-0.008	341.45	0.000
		12	-0.096	-0.410	346.42	0.000

Source: Author's calculation

Having confirmed the validity of the selected baseline model, the next step is to utilize this model to generate nowcasting results for Bhutan's real GDP. To achieve this, we will employ both the Bridge model and the MIDAS model for nowcasting the real GDP.

The bridge equation model integrates various economic indicators, such as lagged GDP values, electricity output, investment, consumption, imports, and manufacturing activity, as regressors to capture their relationship with GDP growth. By applying the estimated coefficients from the bridge equation model to the most recent data available for these explanatory variables for the first quarter of 2024, a nowcast figure of 2.88 percent for 2024Q1 is obtained. This predicted GDP growth rate of 2.88 percent reflects the expected rate of expansion in Bhutan's economy during that quarter, based on historical relationships between GDP and the included economic indicators.

Figure 8. Bridge forecast for Real GDP of Bhutan, 2024Q1 (2.88%)

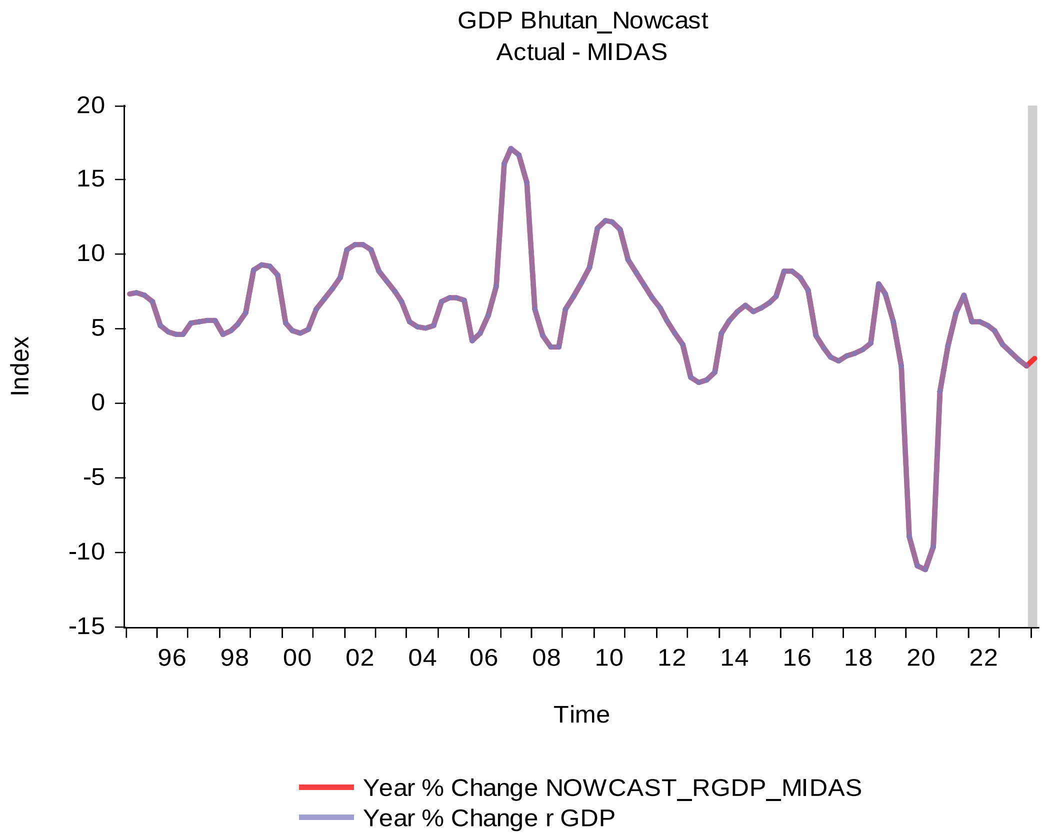


Source: Author's calculation using Bridge estimation

While MIDAS and bridge models share the same base model, MIDAS takes a distinct approach in incorporating high-frequency variables (like monthly data) into the regression. This difference is crucial because it allows MIDAS to reduce the overall number of parameters estimated in the base model, which can become quite large with traditional bridge models (Ghysels, Santa-Clara, & Valkanov, 2004).

Figure 9 illustrates the nowcast estimate of 2.99 percent using MIDAS model, indicating the anticipated growth rate of real GDP for the first quarter of 2024 (2024Q1).

Figure 9 MIDAS forecast for Real GDP of Bhutan, 2024Q1 (2.99%)



Source: Author's calculation using MIDAS estimation

In this research paper, we utilize a nowcasting combination method to evaluate the effectiveness of in-sample forecasts (Timmermann, 2006). This method involves averaging individual forecasts using a custom weighting scheme known as combined forecast. The use of combined forecasts has become increasingly popular in current research due to their tendency to surpass individual forecasts, thus improving overall forecasting accuracy. While different weighting schemes, like inverse mean square error, can be utilized for this averaging process, we opt for simple and trimmed weights. Specifically, each series is assigned a weight of 1/6 to derive a combined forecast, or nowcast, for this study (Timmermann, 2006).

Table 10 Forecast Evaluation

Forecast Evaluation

Sample: 2012Q1 2024Q1

Included observations: 49

Evaluation sample: 2012Q1 2024Q1

Number of forecasts: 3

Combination tests

Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
RGDP_F_FC	16.64611	0.0000
R_GDPF_BRIDGE	60.33777	0.0000
RGDP_F_MIDAS	0.552793	0.5792

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
RGDP_F_FC	779.6029	521.9398	0.307856	0.307935	0.002374	0.252565
R_GDPF_BRIDGE	1131.528	752.5329	0.453807	0.454079	0.003446	0.378884
RGDP_F_MIDAS	599.7564	315.5207	0.175723	0.175725	0.001826	0.187273

Source: Author's calculation using in-sample forecast evaluation

The F-statistics evaluate the null hypothesis that the i^{th} forecast includes all the information present in the remaining nowcasts. In the case of the MIDAS model, we find no evidence to reject this null hypothesis within the nowcast set. This result indicates that the MIDAS nowcast model fully incorporates the information provided by the other models in the set.

The evaluation statistics indicate that the RGDP_F_MIDAS forecast demonstrates the best overall performance, characterised by the lowest RMSE, MAE, MAPE, SMAPE, Theil U1, and Theil U2 values. This suggests that the MIDAS model provides the most precise forecasts for real GDP across the observed timeframe. Additionally, the combination tests reveals that while the RGDP_F_FC and R_GDPF_BRIDGE forecasts possess significant unique information, the RGDP_F_MIDAS forecast does not significantly contribute unique information compared to the others.

7. Conclusion

This study delved into the potential application of the Mixed-Frequency Data Sampling (MIDAS) technique and Bridge estimation methods for the real-time nowcasting of GDP in Bhutan. Through an evaluation of the MIDAS estimation technique against conventional approaches and the identification of suitable high-frequency indicators for incorporation into the model, our research has highlighted MIDAS as a promising estimation technique for GDP nowcasting in Bhutan, providing policy makers with valuable and timely insights.

Nevertheless, certain limitations exist, notably concerning data availability and model accuracy during periods of economic disruption. Future research could explore additional high-frequency indicators as they become accessible and evaluate the model's robustness under diverse economic conditions. This study underscores the potential of nowcasting techniques to enhance Bhutan's economic policymaking by providing more timely and data-driven insights into the country's economic performance. Implementing these techniques and continuously refining the model can significantly benefit Bhutan's economic management and preparedness for future challenges.

To strengthen Bhutan's economic forecasting capabilities, enhancing data collection infrastructure and devising a comprehensive array of high-frequency indicators are recommended. Reinforcing the existing macroeconomic technical team and fostering collaboration with pertinent stakeholders and institutions are essential for the effective utilization of nowcasting techniques. Additionally, investing in the capacity development of economists and analysts, alongside continual refinement of nowcasting models, will further augment informed and efficacious policymaking, thereby fostering sustainable economic growth and resilience.

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