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Moving with the Times: Strengthening Belize's Nowcasting Framework for Relevancy in a Post-COVID-19 World

Marco Chan

Research and Economic Analysis Department
Economic Intelligence Unit

CBB Working Paper
Research and Economic Analysis Department

**Moving with the Times:
Strengthening Belize's Nowcasting Framework for
Relevancy in a Post-COVID-19 World**

Prepared by: Marco Chan
Authorised for distribution by: Emory Ford

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This paper improves the quarterly Gross Domestic Product (GDP) nowcasting framework used by the Central Bank of Belize to account for structural changes in Belize's economy brought on by a rebasing exercise and the volatility induced by the COVID-19 pandemic. Employing a bottom-up approach, the framework utilises 16 Autoregressive Integrated Moving Average with exogenous variables (ARIMAX) models, using the Box-Jenkins (1968) approach, to nowcast industrial value-added components. These are then aggregated to derive a quarterly GDP estimate. The exogenous variables include timely industrial indicators and dummy variables, strategically incorporated to capture the economic fluctuations caused by the pandemic. The results demonstrate a significant improvement in the Mean Absolute Percentage Error (MAPE) for both the pre- and post-pandemic periods. Specifically, the MAPE decreases from 4.1% to 2.5% for 2017Q1 – 2019Q4 and from 8.7% to 3.0% 2020Q1 – 2022Q2, highlighting the enhanced accuracy of the new framework compared to benchmark models. The findings indicate that ARIMAX models offer superior out-of-sample forecasting accuracy and provide valuable insights for policymakers navigating economic shocks and structural adjustments.

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Author's Email Address: marco.chan@centralbank.org.bz

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1.0 Introduction

Since 2017, the Central Bank of Belize has been using a nowcasting framework consisting of 11 linear dynamic industrial models and 34 bridge indicators to estimate Belize's GDP quarterly. Initially developed by Arana (2015), this framework allowed the Bank to produce quarterly GDP estimates within five weeks of a quarter's end, providing stakeholders with a timelier view of economic conditions. In comparison, the Statistical Institute of Belize (SIB) produces its first round of quarterly GDP estimates nearly three months after the quarter under review.

The need to update the nowcasting framework was motivated by the impact of SIB's GDP rebasing exercise in 2022. The rebasing exercise, which used the System of National Accounts (SNA) 2008 compared to SNA 1993, identified seven new industries, rendering the old nowcasting framework obsolete (SIB, 2020). Additionally, the nowcasting model's accuracy plummeted in the wake of the COVID-19 crisis, with the Mean Absolute Percentage Error (MAPE) more than doubling from 4.1% to 8.7%. Its sectoral components, anchored on ordinary least squares (OLS) and autoregressive integrated moving average (ARIMA) models, could not predict the erratic shifts in economic conditions. Consequently, the model's efficacy in forecasting short-term GDP diminished, leading to higher margins of error and reduced reliability of the overall GDP estimate.

To address these challenges, this paper aims to enhance the Central Bank's GDP nowcasting framework to better capture the structural changes, arising from the GDP rebasing exercise, and to model the sharp economic fluctuations, stemming from the COVID-19 shock. This involved an overhauling of the existing 11 sectoral model framework to utilise 16 Autoregressive Integrated Moving Average with exogenous variables (ARIMAX) models, employing the Box-Jenkins (1968) approach. To address the heterogeneous response to the pandemic across industrial categories, dummy variables are strategically incorporated to improve model accuracy. The exogenous variables were guided by the SIB's "*System of National Accounts Documentation*" (2020).

A comprehensive review of the previous and proposed frameworks' performance revealed improvements in the accuracy of quarterly GDP estimates, with the MAPE improving from 6.1% between 2017Q1 and 2022Q1, to 2.1% between the same period. The enhanced precision of the new nowcasting framework should provide the Central Bank with timely insights into the economic landscape and reveal nuanced changes across sectors over time. This granular understanding will enable the identification of sector-specific trends and serve as an early warning system for potential economic imbalances.

The paper is structured as follows: Section II reviews the pertinent literature. Section III covers the methodology employed in constructing the ARIMAX models. Section IV presents empirical results, while Sections V and VI provides a discussion on the results generated and conclusions, respectively.

2.0 Literature Review

2.1 Nowcasting and Evolution of Techniques

Nowcasting, or the prediction of current economic conditions based on available data, plays a crucial role in informing timely policy decisions and providing stakeholders with up-to-date assessments of economic performance. The importance of accurate and efficient nowcasting frameworks has been underscored by recent events such as the COVID-19 pandemic, which caused unprecedented volatility and structural shifts in economies worldwide. In recent years, there has been a growing body of research focused on developing and refining nowcasting methods. Studies have explored various approaches, including bridge models, dynamic factor models, and mixed-frequency data analysis, to enhance the accuracy and timeliness of GDP estimates. Since Giannone, Reichlin, & Small (2006) introduced a formal process for updating nowcasting frameworks, numerous techniques and tools have been developed to improve the accuracy and timeliness of estimates.

2.2 Bottom-Up Approach to Nowcasting

Previously, the Central Bank relied solely upon a bottom-up approach, aggregating 11 sectoral bridge models to produce a quarterly GDP estimate based on the work of Arana (2015). Although Arana (2015) preferred indicator models, sectoral models were used due to limits on data availability and the added benefit of observing nuanced trends within GDP's various components through the disaggregation, as was found to be the case in Kaustubh, Bhadury, & Ghosh (2024) and Dias, Pinheiro, & Rua (2016).

Several studies suggest that a bottom-up approach to nowcasting GDP components for subsequent aggregation can enhance the accuracy of estimates. For instance, Dias, Pinheiro, and Rua (2016) employed factor models to project expenditure-side components of GDP and found that performance outstripped that of univariate benchmark models. Similarly, Hahn and Skudelny (2008) adopted a production-side approach to forecast GDP sub-categories, demonstrating not only improved accuracy but also the valuable insights gained from understanding the co-movements of underlying drivers of economic growth. Moreover, the bottom-up approach also provided a means for accounting for sector-specific shocks since abnormal growth levels in one component of GDP could be easily identifiable and (Hahn & Skudelny, 2008). This characteristic was explored following the pandemic as researchers sought to capture the impact of the pandemic across various economic sectors. Kaustubh, Bhadury, and Ghosh (2024) produced a production-side nowcast in which the impact of the pandemic was accounted for within each sub-categorical estimate. This was done using dummy variables representing the onset of the pandemic, which were found to be statistically insignificant for select subcategories and highly significant for others (Kaustubh, Bhadury, & Ghosh, 2024).

2.3 Challenges to Nowcasting: Structural Changes and Economic Shocks

Relationships between indicators and GDP can change over time, owing mainly to large structural shifts, as noted in Hahn and Skudelny (2008). In developing countries, rebasing exercises, often result in stark changes to the fundamental structure of an economy and underlying drivers of growth. For example, Akpan & Udofia (2017) found that Nigeria's largest contributor to growth had shifted away

from manufacturing to services in their study following a rebasing exercise. The consequences of this were profound for Nigeria, as was also the case for Belize.

Bridge and mixed data sampling (MIDAS) models failed to capture the magnitude of impact on GDP due to their primary premise of capturing the average behaviour of variables over a period of time (Faroni, Marcellino, & Stevanovic, 2022). This was widespread as Arana (2015), Cascaldi-Garcia, Luciani, & Modugno (2023), Kaustubh, Bhadury, & Ghosh (2024), and others pointed out the ephemeral nature of the explanatory power for some indicators. The onset of the COVID-19 pandemic also severely disrupted the effectiveness of sectoral models and other traditional forecasting methods, as they failed to capture the impact of sharp fluctuations on GDP (Cascaldi-Garcia, Luciani, & Modugno, 2023).

2.4 Innovations in Nowcasting in Response to the Pandemic

Incidentally, the pandemic catalysed growth in research within the field of nowcasting resulting in a growing body of work on the subject matter. The focus of these studies were multifaceted, ranging from the recalibration of models and frameworks using more sophisticated econometric tools as was the case in Cascaldi-Garcia, Luciani, & Modugno (2023), to the reworking of simpler approaches such as Dias, Pinheiro, & Rua (2016), as well as the incorporation of alternative data sources like Nakazawa (2022) and Kaustubh, Bhadury, & Ghosh (2024). The pandemic severely impacted the ability of nowcasting models to assess the severity of the economic downturn. This was stated by Faroni, Marcellino, & Stevanovic (2022) and Nakazawa (2022), in observance of their respective bridge and unrestricted mixed data sampling (UMIDAS) models, which failed to predict the depth of the downturn due to a lack of timely, statistically significant data. The same holds true for the more sophisticated Dynamic Factor Models (DFM), which were widely employed during the pandemic.

Most models were not equipped to capture the magnitude of the pandemic without significant adjustment through the incorporation of alternative high-frequency data sources such as in Cascaldi-Garcia, Luciani, & Modugno (2023) and Kaustubh, Bhadury, & Ghosh (2024). Machine learning techniques have demonstrated some superiority in predicting both the occurrence and depth of contraction brought on by anomalous occurrences. In Maccarrone, Morelli, & Spadaccini (2021), traditional ARIMA and SARIMAX models were pitted against a machine learning model, which emerged as the most accurate model when nowcasting one quarter ahead, with significantly smaller margins of error. Similarly, a study across six European countries, Dauphin, et al. (2022) found that machine learning models surpassed benchmark and DFM models in reducing forecast errors during the pandemic in most countries. Barrios et al. (2021) furthered the discourse in Belize by introducing six machine learning models, including lasso regressions, random forest algorithms, and neural networks. These models generate a singular quarterly GDP estimate, compiled into an ensemble figure based on weights derived from the inverse of RMSE produced by each model (Barrios, Martin, Escobar, Pena, & Leslie, 2021).

Nevertheless, the performance of traditional models cannot be discounted, as Maccarrone, Morelli, & Spadaccini (2021)'s SARIMAX models outperformed the machine learning models when looking at longer horizons and with the introduction of covariates. It is important to note that the current framework utilised by the Bank is a bottom-up approach employing 11 bridge sectoral models to produce one estimate. This approach, distinct from both Maccarrone, Morelli, & Spadaccini (2021) and Barrios et al. (2021), provides a more nuanced observance of the economy. Such approaches to nowcasting are rare but not unprecedented.

2.5 Theoretical Framework for the Current Study

The use of dummy variables to capture the impact of the pandemic on economic activity has been explored to varying degrees in the years since the outbreak. In their study of addressing outliers within their vector autoregressive (VAR) models, Carriero et. al (2024) opted to use dummy variables to capture the monthly impact of the pandemic, which absorbed the VAR residuals, improving the fitness of the model. Meanwhile, Furceri et. al (2021), utilise dummy variables within their models to capture multiple pandemics within a 20-year span and assess the most recent pandemic's impact on inequality. Nevertheless, the most relevant study that mirrors the efforts of this paper remains Kaustubh, Bhadury, and Ghosh's (2024). Their use of dummy variables to capture the pandemic's effect within a bottom-up approach to nowcasting GDP, combined with Maccarrone et al. (2021)'s ARIMAX-based approach to nowcasting forms the theoretical backbone of this paper.

3.0 Methodology

3.1 Overview

This paper aims to enhance the Bank’s GDP nowcasting framework to accurately capture recent structural changes brought on by a recent rebasing exercise and effectively model the impact of the pandemic. Within this section, the application of the Box-Jenkins (1968) three-step approach allowed for the creation of 16 ARIMAX industrial models. These were then aggregated to nowcast quarterly constant GDP.

To capture the heterogenous effects of the pandemic on the various industries, two dummy variables were created. These variables represent the initial downturn and subsequent rebound in GDP activity during and after the pandemic¹. The inclusion of these dummies, either individually or in combination, was informed by Chow breakpoint tests conducted for each industry. The exogenous component in each of the 16 models were then drawn identified from the SIB’s “*System of National Accounts*” documentation. Following these steps, the industrial models were estimated, with relevant diagnostics conducted.

3.2 Industrial Models

3.2.1 Selection of Industrial Groupings

Following the SIB’s 2022 GDP rebasing exercise, the number of industrial classifications rose from 11 to 21, see Table A1. In this paper, the 11 additional industries were aggregated into six industrial groupings². This study diverges from the previous framework’s structure of modelling each industrial classification for two reasons. The first was the unavailability of timely variables. The second was lack of utility gained from nowcasting industries with miniscule waited contributions to GDP. Table 1 below identifies the new industrial groupings.

Table 1: Components of Industrial Grouping

Industrial Components	Grouping Name
Mining	Mining
Water Supply	Water Supply
Real Estate Activities	Real Estate Activities
Professional Scientific and Technical Activities	Professional and Administrative Activities
Administrative and Support Service Activities	
Education	Education and Health Activities
Human Health and Social Work Activities	
Information and Communication	Other Activities
Arts, Entertainment, and Recreation	
Other Service Activities	
Activities of Households as Employers	

¹ Q1 2020 – Q4 2021

² Due to the absorption of subcategory “*Fishing*” into “*Agriculture, Forestry, and Fishing*,” only 10 of the initial 11 industrial categories remained, with 11 new categories identified.

The grouping of eight industries together to form three categories resulted from an investigation into the explanatory power of the selected exogenous variables in determining the gross value added (GVA) estimates of the industries. Given that variables for the six industries were not available in a timely manner, the suitability of various alternate quarterly and monthly indicators were assessed via correlation testing for the eight industries. This was done according to the SIB's guidelines provided in the "*System of National Accounts Documentation*" (2020), which outlines the methods and indicators used to compile GDP and its industries. From here, industries that shared explanatory variables were combined.

As a result, "*Professional Scientific and Technical Activities*" and "*Administrative and Support Services Activities*" were aggregated into "*Professional and Administrative Services*," with GST, business tax, and BPO inflows proven to be significantly correlated variables. Similarly, "*Education*" and "*Human Health and Social Work Activities*" were combined into "*Education and Health Activities*," sharing current fiscal expenditure as an explanatory variable. The largest amalgamation was of the four categories "*Information and Communication*," "*Arts, Entertainment, and Recreation*," "*Other Service Activities*," and "*Activities of Households as Employers*" into "*Other Services*," which found tourism arrivals to be the most appropriate variable.

3.2.2 Data Selection

For the 16 proposed industrial models, 42 exogenous explanatory variables were used. All indicators were used by the SIB, as shown in their "System of National Accounts" (SIB, 2020) documentation, to generate estimates of value-added output across the industries. To directly nowcast 10 industrial models, 12 variables are utilised, as shown in appendix table A2. The remaining six models use five indices shown in Table 2. The indices were constructed using 30 variables in accordance with specifications provided by the SIB and are standardised to the base year of 2014. The construction of these indices arose to avoid the issue of overfitting the models.

Table 2: Industrial Models Utilising Indices as Exogenous Variables

Index	Industrial Model
Agricultural Index	Agriculture, Forestry, and Fishing
Manufacturing Index	Manufacturing
Tourist Arrival Index	Hotels and Restaurant Activities Other Service Activities
Transportation Index	Transportation
Professional and Administrative Services Index	Professional and Administrative Activities

3.2.3 Dummy Variables and Chow Breakpoint Test

As previously mentioned, to capture the effects of the pandemic on the 16 industrial categories two dummy variables were created. The first, “COVID 2020” captures the initial downturn in economic activity between the first quarter of 2020 and the first quarter of 2021. The second, “COVID 2021” encapsulates the period of high GDP growth noted between the second quarter of 2021 and first quarter of 2022. To determine the placement of the variables, a Chow Breakpoint Test was conducted on each of the 16 industrial groupings to determine when each industry specific breakpoint occurred. The equation for the test given as:

$$\frac{RSS - (RSS_1 + RSS_2)}{RSS_1 + RSS_2} \times \frac{T - 2k}{k} \quad (1)$$

Where RSS is the sum of squared residuals of the sample series, RSS_1 is the sum of squared residuals before and up to the identified break date, RSS_2 is the sum of squared residuals at and after the identified break date, T is the number of observations, and k is the number of regressors in the equation. The results of this test, dictating which dummy variables were included in each industrial model is found below in Table 3.

Table 3: Results of Chow Breakpoint Test

Industrial Groupings	COVID2020	COVID2021
Agriculture, Forestry, and Fishing		
Mining	√	
Manufacturing		
Electricity	√	
Water Supply	√	√
Construction	√	√
Wholesale and Retail Trade	√	√
Hotels and Restaurant Activities	√	
Transportation		√
Financial Activities	√	√
Real Estate Activities	√	√
Professional and Administrative Activities	√	√
Public Administration and Defence Activities	√	√
Education and Health Activities		
Other Service Activities		√
Taxes and Subsidies		

3.3 ARIMAX Model and Components

An extension of the ARIMA model, the ARIMAX model incorporates the influence of one or more exogenous variables in estimating forecasts. The three parameters of the ARIMA model (p,d,q) are as follows:

The autoregressive AR(p) component is defined as: 3.4 ARIMAX Model Fitting

$$\begin{aligned} Y_t &= \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \varepsilon_t \\ &= \sum_{j=1}^{\phi} \phi_j y_{t-j} + \varepsilon_t \end{aligned} \quad (2)$$

Where Y_t is the current observation, y_{t-j} are the past observations, ϕ is the autoregressive order of the process with coefficients ϕ_j , and ε_t is the white noise component. When incorporating a lag operator, the $AR(p)$ takes the basic form:

$$y_t = \sum_{j=1}^{\phi} \phi_j L^j y_{t-j} + \varepsilon_t \quad (3)$$

Where $\phi(L) = 1 - \sum_{j=1}^{\phi} \phi_j L^j$ is defined as the lag polynomial that characterises the AR process. The addition of a mean to the model produces the AR model below.

$$\phi(L)(Y_t - \mu_t) = \varepsilon_t \quad (4)$$

The moving average $MA(q)$ component of the ARIMAX model is comprises of:

$$Y_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_i \varepsilon_{t-i} \quad (5)$$

$$\begin{aligned} &= \varepsilon_t + \sum_{j=1}^q \theta_j \varepsilon_{t-j} \\ &= \theta(L) \varepsilon_t \end{aligned}$$

Where ε_t is the current disturbance, ε_{t-j} are the past disturbances, θ_i are the parameters of the MA model, and $\theta(L)$ are the moving average polynomial that characterises the MA process. When both AR and MA processes are combined, they form the ARMA equation:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \dots - \theta_q \varepsilon_{t-q} \quad (6)$$

$$p(L)(Y_t - \mu_t) = \theta(L) \varepsilon_t$$

Thus, when incorporating the integrated order $I(d)$, an ARIMA (p, d, q) is formed as:

$$p(L)(1 - L)^d (Y_t - \mu_t) = \theta(L) \varepsilon_t \quad (7)$$

Lastly, the addition of exogenous variables reveals the final ARIMAX model form as:

$$p(L)(1 - L)^d (Y_t - \mu_t) = \beta_n x_{n,t} + \theta(L) \varepsilon_t \quad (8)$$

Where $\beta_n x_{n,t}$ is the coefficient of the exogenous variable(s).

3.4 ARIMAX Model Fitting

For the 16 ARIMAX models, the Box-Jenkins three-stage approach was implemented, namely model identification, estimation, and diagnostic checking. The 16 industrial series were found to be non-stationary, and their appropriate AR and MA orders were identified. Following this, the most appropriate model is selected for each industrial grouping after comparison utilising the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan-Quinn Information Criterion (HQIC). Thereafter, following forecasting of the models, the models are checked for invertibility. Lastly, to evaluate the results, the measures of forecast accuracy are set forth.

3.4.1 Identification & Estimation

The properties of the 16 industrial GVAs were analysed for stationarity through graphs and correlograms generated for each. None of the variables were found to be stationary. Following this, Augmented Dickey Fuller tests (ADF) were conducted for each to identify the level at which the variables are stationarity. The results are summarised in Table 4 below. the Autocorrelation function (ACF) and Partial Autocorrelation function (PACF) are then utilised to determine the number of MA and AR terms, respectively. This is also highlighted in Table 4.

Table 4: Differencing and AR/MA Order Results for Industrial Groups

Industrial Groupings	Differencing	AR Order	MA Order
Agriculture, Forestry, and Fishing	1st	2	2
Mining	2nd	1	1
Manufacturing	1st	2	2
Electricity	2nd	2	1
Water Supply	2nd	2	1
Construction	2nd	8	1
Wholesale and Retail Trade	2nd	4	1
Hotels and Restaurant Activities	2nd	2	2
Transportation	1st	1	1
Financial Activities	2nd	6	1
Real Estate Activities	1st	4	6
Professional and Administrative Activities	1st	3	1
Public Administration and Defense Activities	2nd	1	4
Education and Health Activities	1st	1	4
Other Service Activities	2nd	1	1
Taxes and Subsidies	2nd	1	1

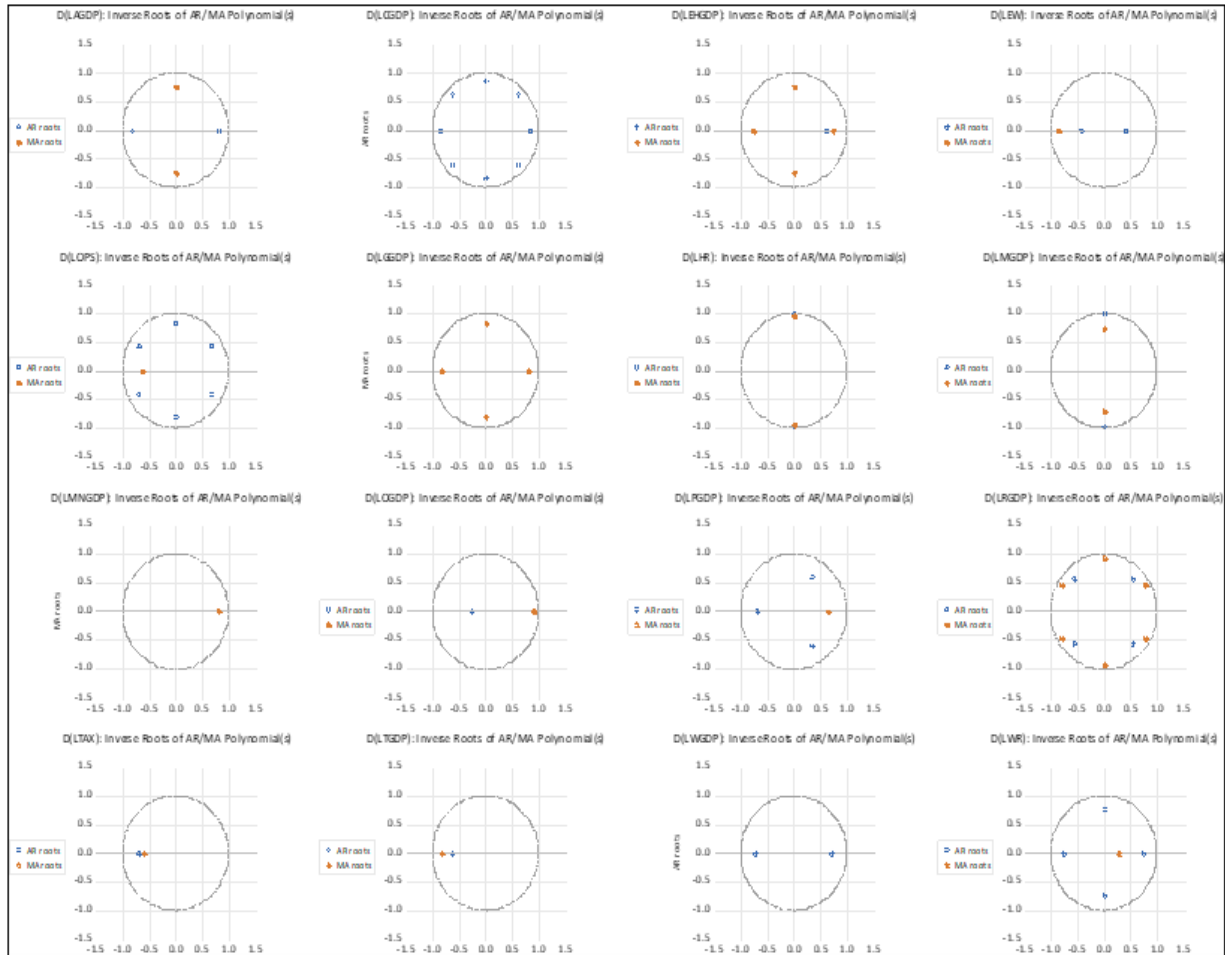
3.4.2 Estimation

Following the identification of possible suitable models for each of the 16 proposed, the models were estimated using the maximum likelihood method and compared. Those with the lowest AIC, BIC and HQIC values were selected for forecasting. The AR and MA components were found to be significant across the 16 models.

3.4.3 Diagnostics

To ensure the selected models satisfy the requirements for a stable univariate process, the ACF and PACF plot of residuals are evaluated, and unit root tests are conducted. The Ljung-Box Q statistics are analysed for each of the 16 models to ensure residuals are white noise. Thereafter, the results of the unit root test for serial correlation across the 16 models showed that no root of the estimated models fell out of the -1 and +1 bounds, therefore satisfying the requirement of invertibility³. The results of this test can be found in Figure 1 below.

Figure 1: Roots of Characteristics Polynomial for 16 Industrial Models



³ Invertibility is a desirable property for MA models in time series analysis. It ensures uniqueness, aids in estimation, and can improve forecasting performance.

3.4.4 Assessment of Forecast Accuracy

To assess forecast accuracy, three methods are utilised to test different aspects of the results of the models. The first method is the Root Mean Square Error (RMSE) statistic, which measures the difference between the predicted and estimated values by analysing the standard deviation of the residuals. It is represented by the equation:

$$\sqrt{\sum_{t=T+1}^{T+h} (\psi_t - \gamma_t)^2 / h} \quad (9)$$

Where the forecasted value is denoted by ψ_t , the actual value is γ_t , the forecast sample is $T+h$, and the period is defined as t .

The second method is the MAPE approach, which represents the average of the absolute percentage errors of each entry to calculate the accuracy of forecasted values in comparison to actual values. It is represented by the equation:

$$100 \sum_{t=T+1}^{T+h} \left| \frac{\psi_t - \gamma_t}{\gamma_t} \right| / h \quad (10)$$

Lastly, the Theil U2 coefficient is used to determine the forecast quality and adequacy of the models. It is represented as:

$$U_2 = \frac{\sqrt{\frac{1}{n} \sum_{t=1}^n (\psi_t - \gamma_t)^2}}{\sqrt{\frac{1}{n} \sum_{t=1}^n \gamma_t^2}} \quad (11)$$

In the first two methods, a value closer to 0 is desirable to show forecast accuracy. In the Theil U2 coefficient, 0 is also desirable to show accurate forecasts. However, a Theil U2 value equal to or above one denotes a weak model.

4.0 Results

The GVA of 16 industrial ARIMAX models for the period 2017Q1-2022Q4 were forecasted and aggregated to arrive at an estimate of quarterly GDP, which were then compared to actual estimates. Thereafter, forecast accuracy was assessed utilising the RSME, MAPE, and Thiel U2 coefficient. The utilisation of all three methods was implemented with the goal of capturing the most holistic view of the forecast performance of the models. The RMSE would indicate whether large errors are present within the forecast, while the MAPE adds the dimension of overall accuracy relative to the scale of the data. The Thiel U2 coefficient would contribute an assessment of the model's ability to capture the dynamics of change in the variable.

It was found when assessing the RMSE and MAPE that three of the 16 forecasts had higher than average test statistics, respectively, while a total of five did not fall within acceptable bounds when gauging the Thiel U2 coefficient. Interestingly, only one of these seven models were found to have all three of the unfavourable statistics concurrently.

4.1 Aggregated ARIMAX Model Results

The natural logarithm values generated by the 16 industrial models were expanded and aggregated for comparison to the actual estimates. These results are summarised in the figures below. When aggregated, the RMSE for the forecast period of 2017Q1 – 2022Q4 was 2.8%, while the MAPE was 2.5%, indicating relatively accurate forecasts.

Figure 2: Forecasted GDP Percent Change Versus Actual GDP Percent Change

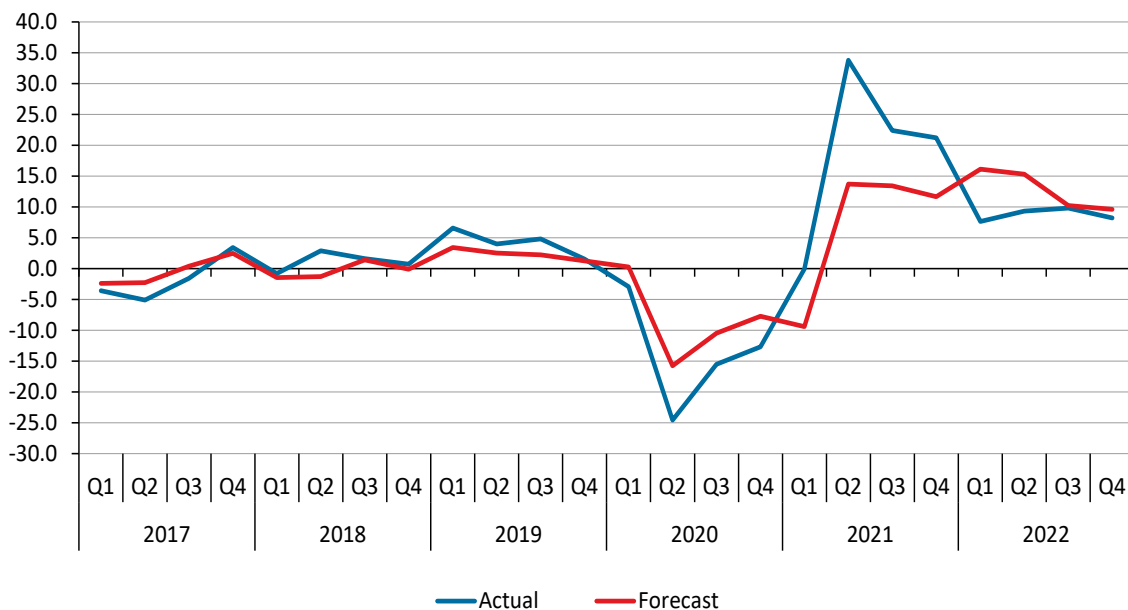
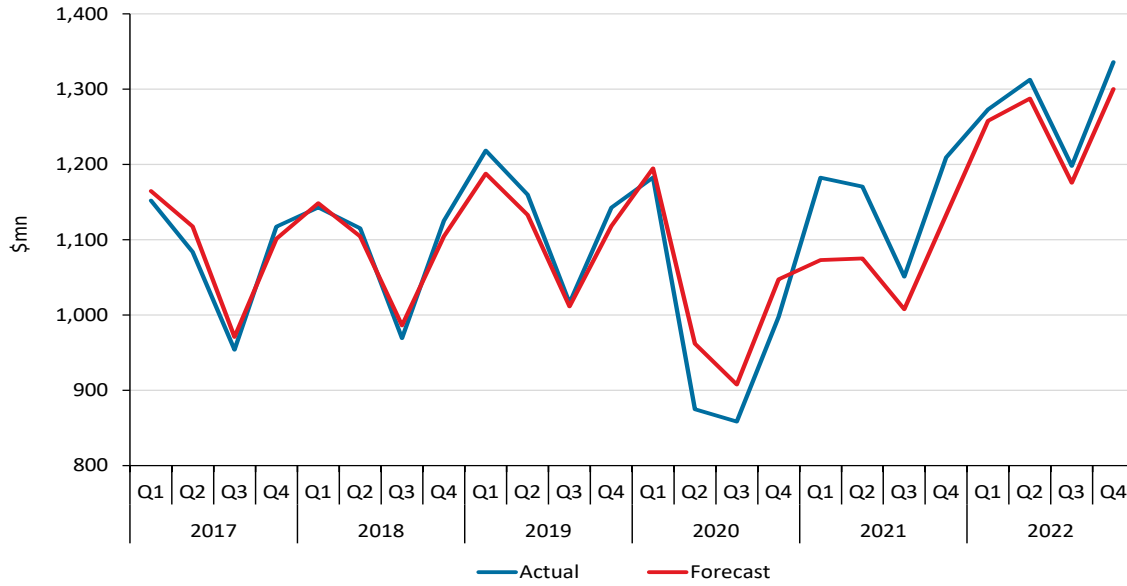


Figure 3: Forecasted GDP Value Versus Actual GDP Value



The models performed best in estimating the GVAs of the pre-pandemic era, as shown in Table 5, with the RMSE totalling 2.5% of GDP between 2017 and 2019, compared to 3.0% between 2020 and 2022. The MAPE reflected a similar narrative, averaging 2.3% in the pre-pandemic era, and 2.7% in the post-pandemic era. Volatility towards the end of the time series can be inferred from the disaggregated examination of the industrial models.

Table 5: Aggregated Annual RMSE and MAPE

	RMSE	MAPE
2017	23.6	2.0
2018	31.1	2.6
2019	27.6	2.3
2020	27.7	2.6
2021	38.2	2.9
2022	33.7	2.6

4.2 Assessment of *ARIMAX* Model Forecast Accuracy

The 16 *ARIMAX* models forecasted the period 2017Q1 to 2022Q4 and yielded results that were tested for forecast accuracy, summarised in Table 6 below. The results indicated mixed results when analysing each of three unique measures of forecast accuracy. A description of these various combinations of results is provided in Table 7.

Table 6: Measure of Forecast Accuracy by Industrial Model

Industrial Groupings	RMSE	MAPE	Thiel U2 Coefficient
Agriculture, Forestry, and Fishing	0.16	3.14	0.31
Mining	0.24	6.83	1.03
Manufacturing	0.11	1.98	0.29
Electricity	0.25	7.45	0.84
Water Supply	0.04	1.38	0.69
Construction	0.15	3.31	1.59
Wholesale and Retail Trade	0.05	0.72	0.56
Hotels and Restaurant Activities	0.19	10.34	0.09
Transportation	0.12	2.75	0.41
Financial Activities	0.04	0.65	1.38
Real Estate Activities	0.01	0.18	1.63
Professional and Administrative Activities	0.16	3.33	0.77
Public Administration and Defence Activities	0.04	0.78	0.61
Education and Health Activities	0.03	0.40	0.39
Other Service Activities	0.12	2.26	1.49
Taxes and Subsidies	0.06	1.03	0.66

Table 7: Forecast Accuracy Conditions

RMSE/MAPE Condition (Level)	Thiel U2 Coefficient Condition (Direction)	Result
Low RMSE/MAPE	Low Thiel U2 Coefficient	Model robustly estimates the general level and direction of a variable
Low RMSE/MAPE	High Thiel U2 Coefficient	Model estimates the general level of a variable but not the direction and magnitude of changes
High RMSE/MAPE	Low Thiel U2 Coefficient	Model estimates the direction and magnitude of changes but not the general level of the variable
High RMSE/MAPE	High Thiel U2 Coefficient	Model does not estimate the general level or the direction and magnitude well

Analysis of the RMSE, estimated from the difference between the actual and forecasted values, revealed that all models held relatively low values. While the RMSE does not have a standard range to measure results by, the general rule dictates that the closer the value is to 0, the more accurate the forecast is. When testing for outliers, the RMSEs of three models were identified, “*Mining*”, “*Electricity*”, “*Hotels and Restaurants*”.

When the same exercise was carried out for the MAPE statistics, the previous three outliers reappeared. Nevertheless, all MAPE statistics except for one, fell within the acceptable range of $\mu(Y_t) < 10\%$ as per Lewis (1982).

The Thiel U2 coefficient is a statistic that measures how well a model predicts changes in a variable. The closer the value is to 0, the better the forecast performance, however, if the value exceeds 1.0, the forecast is deemed inferior to a simple no change naïve forecast. From the industrial forecasts, five were identified with a Thiel U2 coefficient exceeding 1.0, with three surpassing the acceptable range by large margins. These were “*Construction*,” “*Real Estate Activities*,” and “*Other Service Activities*.”

Incidentally, only the “*Mining*” model produced forecasts in which the RMSE and MAPE were outside the acceptable bounds, and their Thiel U2 coefficient surpassed the 1.0 acceptable range, albeit by a marginal level. This suggests that the model is poorly estimating the general level of the variable and the direction and magnitude of changes. Thus, four forecasts failed to meet expectations in only one test, two failed in two tests, and only one failed in all three tests. Nine of the forecasts produced excellent results, as identified by their RMSE, MAPE, and Thiel U2 coefficients. Notably, the worst performing models contributed the least to GDP. These results can be summarised in Table 8 below along with their contribution to GDP.

Table 8: Summary of Forecast Accuracy

Number of Forecast Models	Number of Tests Failed	Contribution of Industries to GDP
1	3	2.4%
2	2	7.8%
4	1	23.9%
9	0	66.0%

4.3 Overview of Dummy Performance

For quite a few of the models, the dummy variable was deemed statistically insignificant. However, it was noted that without them, the models failed to capture the impact of COVID. The p-value used to assess statistical significance was geared towards consistent long-term relationships. Thus, due to the nature of the shock, it registered a high p-value. Nevertheless, they were included, as practical significance trumps statistical significance, especially when considering that the RMSE, MAPE, and Thiel U2 coefficients were significantly improved when including one of or both dummy variables. The issue of overfitting is addressed by the fact that the dummies are the only variable with high p-values within the models.

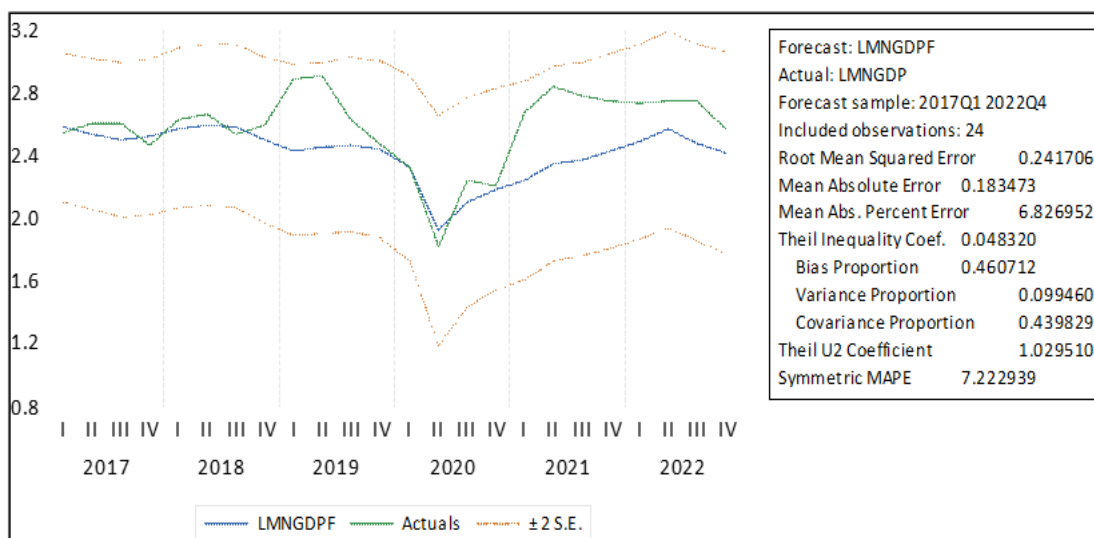
Overall, the inclusion or exclusion of the dummy variables within each required sectoral model was evaluated individually. Within the “*Wholesale and Retail Trade*” industrial grouping, COVID affected both 2020 and 2021 according to the breakpoint test. However, apart from being statistically insignificant, it did not improve the R square or adjusted R square. Nevertheless, it did improve the Theil U2, MAPE, and RMSE by marginal levels. Thus, its inclusion in the model was dubious at best and ultimately included. For “*Transportation*,” the COVID2021 dummy was found to not contribute to any sort of improvement in the model. Thus, despite its suggested inclusion based on the breakpoint test, it was removed. This was also the case for the “*Other Service Activities*” and “*Mining*” industrial groupings. In “*Professional and Administrative Activities*”, only the COVID2020 dummy contributed to the improvement of the model leading to the removal of the COVID2021 variable.

5.0 Discussion

5.1 Industrial Model Performance

The worst performing model was “*Mining*,” which did not forecast the general level or magnitude and direction of the dependent variable. This can be attributed to a few reasons. The explanatory variable ‘oil production value’ was chosen as the better alternative indicator for use in the sectoral model, as financial data for crude oil extraction, oil exploration, and mining of minerals are not available on a high frequency basis. The indicator was found to be highly correlated with the GDP category but not total GDP and its inclusion in the model alongside the COVID2020 dummy variables, which served to capture the structural breaks following the pandemic, yielded weak results. A high MAPE highlighted the indicator’s unpredictability in estimating movements in the category, which was reinforced when analysing the RMSE level. Lastly, the Theil U2 coefficient indicated a poorly performing model. Nevertheless, given the category’s low contribution to GDP (2.3%), and the lack of alternative indicators, the results were accepted. The full dynamic forecast results for the model are outlined in Figure 4 below.

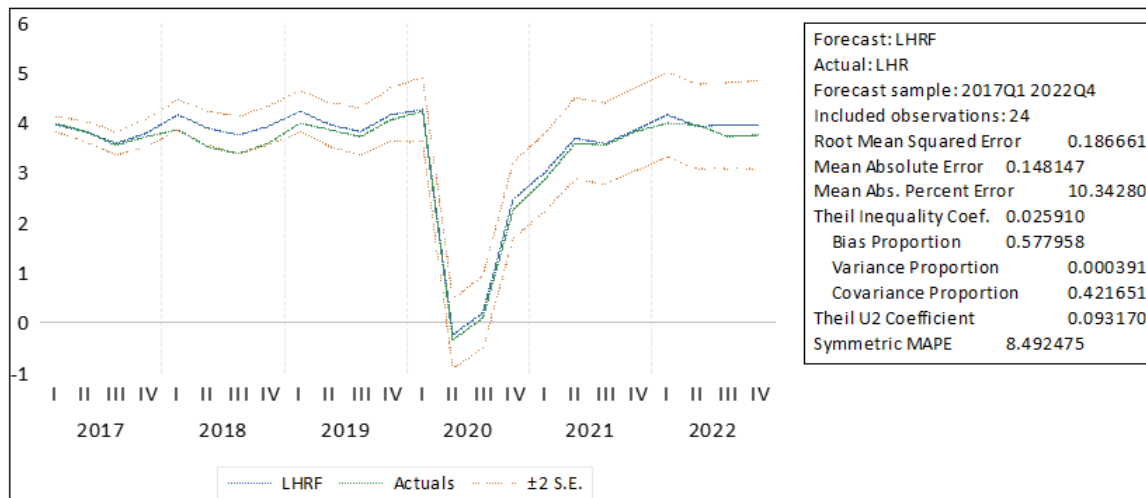
Figure 4: Dynamic Forecast Results for Mining Industrial Model



Of the two models which did not meet the requirements of two tests, “*Hotels and Restaurants*” performed the worst. Despite the model capturing the direction and magnitude of changes, it was unable to capture the general level of the variable. The index “*Tourist Arrival Index*” selected to nowcast “*Accommodation and Food Service Activities*” produced a high correlation coefficient when tested against the GVA. Thus, the indicator provides an accurate measure of activity in the GDP category. Nevertheless, as a substitute for actual expenditure on accommodation, food, and beverage services compiled annual by the SIB, the indicator did not sufficiently capture the dynamics of a given quarter, leading to the high RMSE/MAPE score. It is suspected that the dynamic nature of spending, particularly changes in average expenditure, cannot be accurately captured by arrival figures alone. Thus, this led to significant differences between actual and forecasted values, despite the model’s

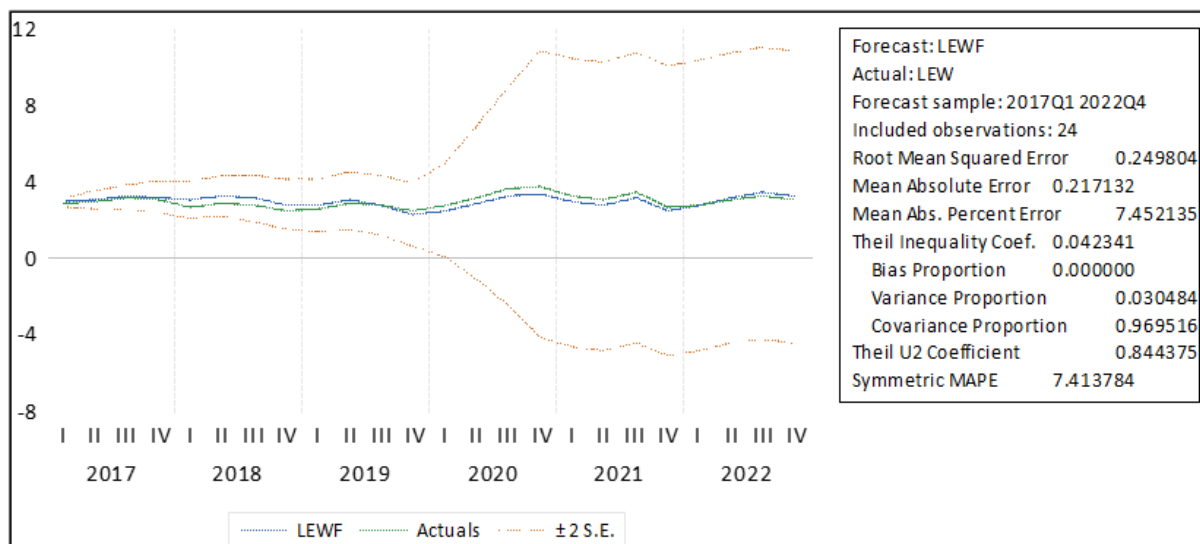
capture of the general trend, as seen in Figure 5 below. The inclusion of dummy variables for 2020 helped to account for the structural break brought on by the event.

Figure 5: Dynamic Forecast Results for Hotel and Restaurants Industrial Model



By Lewis' (1982) metric, the forecast for "Electricity" had an acceptable MAPE score, below 10%. Nevertheless, when plotted, its RMSE and MAPE proved to be outliers, despite having an appropriate Thiel U2 coefficient. As was the case with "Mining," the lack of alternative variables led to only one explanatory variable, Electricity Generation and the COVID2020 dummy to be used in the sectoral model. However, the results were deemed acceptable as the general direction and magnitudes of changes were well estimated. Thus, it included in the overall calculation of total real GDP. Notably, in terms of average contribution to GDP between 2000 – 2022, "Electricity" was the smallest GDP category with a high MAPE. The results are presented in Figure 6 below.

Figure 6: Dynamic Forecast Results for Electricity Industrial Model



From Table 6, four models were identified with unacceptable Thiel U2 coefficients above 1.0. According to theory, this would make the forecast models unacceptable as they do not capture the direction and magnitude of changes. However, they all produced low RMSE and MAPE levels, indicating they estimate the forecasted GVA level to a sufficient degree. Thus, the acceptance of these results depended solely on the specific goals and priorities of this study.

This goal is defined as capturing the general level of the variable for aggregation to nowcast total GDP for a given quarter. With these considerations accounted for, the models are accepted solely based on these factors:

1. The total GDP forecast displays highly accurate results, this is expected given that the three models with the highest U2 coefficients only contribute to 10.1% of GDP.
2. The lack of timely indicators identified for use within the industrial models.
3. That revisions to these models will be forthcoming, either through an adjustment in the model structure, the inclusion of alternative data, or the incorporation of newly available exogenous variables.

5.2 Overview of Previous Model Framework

To demonstrate the improvement of the new framework of models, they are compared in the subsequent sections.

The previous nowcasting framework utilised a bottom-up sectoral approach to aggregate 11 sectoral estimates to produce a quarterly GDP forecast. Despite Arana's (2015) preference for indicator models, the bridge ARMA approach was chosen from the options presented as it provided a more comprehensive explanation of the underlying drivers of economic growth. The models captured all the major subcategories of GDP, with all three major sectors (the primary, secondary, and tertiary sectors) accounted for.

5.2.1 Composition of Previous Models

The 11 bridge models were constructed as per Arana (2015), utilising a combination of OLS and ARMA/ARIMA models and bridge equations. Bridge equations are linear regression models that use high-frequency indicators to connect to a lower-frequency dependent variable. The model then uses the temporally aggregated values as regressors in the equation to obtain forecasts of the low-frequency variable.

Two models, “*Agriculture*” (AGDP) and “*Other Private Services*” (OPS), utilised OLS due to their unique variable parameters and followed the model:

$$Y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \dots + \beta_p x_p + \epsilon_i \quad (1)$$

Where y_i is the dependent variable to be determined, β_0 is the intercept, $\beta_1 \dots \beta_n$ is the coefficient, and $x_1 \dots x_n$ are the independent variables.

The remainder of the sectoral models employed an ARMA approach, defined as:

$$Y_t + c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \theta_1 T_{t-1} + \theta_2 T_{t-2} + \dots + \theta_q T_{t-q} + \epsilon_t \quad (2)$$

Where Y_t is the value of the time series at time t , the constant term is defined as c , $\phi_1, \phi_2, \dots, \phi_p$ are the autoregressive coefficients at the order p , the moving average coefficients are $\theta_1, \theta_2, \dots, \theta_q$ at the order q , while ϵ_t represents the error term at time t .

5.2.2 Model Performance

Over the five-year period, following the implementation of the nowcasting framework, 21 quarterly forecasts were conducted. From the estimates, it was observed that the Mean Absolute Percentage Error (MAPE) stood at 6.1%, while the Root Mean Square Error (RMSE) equalled \$47.2mn or 6.9% of the average actual GDP, and the Mean Absolute Deviation (MAD) totalled \$8.1mn or 1.2% of the average actual GDP. Given its ease of interpretation, this section will focus on the MAPE value and errors. According to Lewis (1982), MAPE results with values of less than 10.0% are defined as highly accurate forecasts. Thus, model outturns will be weighed against this metric.

As observed in Figure 8, discrepancies between the pre-rebasing GDP growth rate and the forecasted GDP growth rates became more pronounced in mid-2019, leading to the onset of the COVID-19 pandemic. Five of the 11 sectoral models displayed high MAPE values, as noted in Table 9, with the categories “*Fishing*,” “*Hotels and Restaurants*,” and “*Producers of Government Services*” recording consistent double-digit error values. Basic nowcasting principles stress the need for constant updates given the ever-changing relationship between indicators and GDP (Bragoli, Metelli, & Modugno, 2014). In sectoral forecasting, this deterioration of the explanatory power variables can be ascribed to idiosyncratic forces affecting the movement of small components of GDP (Dias, Pinhiero, & Rua, 2016). However, based on trend analysis and informed judgment, it was found that the underlying relationships between dependent and independent variables shifted for the five sectoral models, resulting in larger discrepancies.

Figure 7: Comparison of GDP Results for the Initial Nowcasting Framework

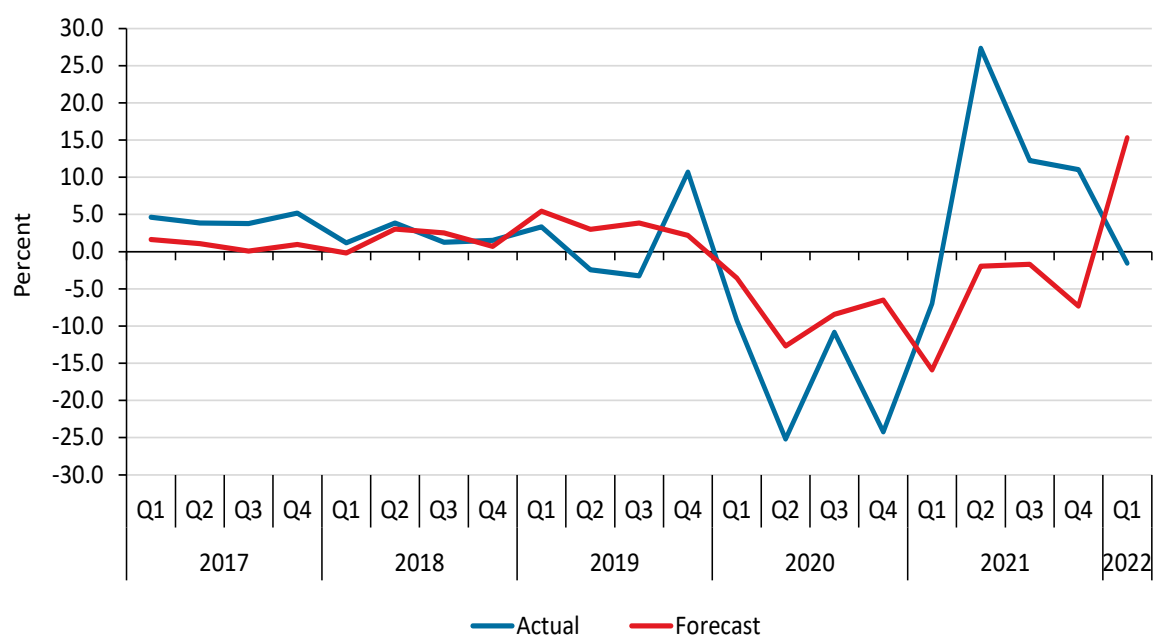


Table 9: Mean Absolute Percentage Error for Sectoral Models in Initial Nowcasting Framework (2017Q1 - 2022Q1)

	MAPE
Agriculture, Hunting, and Forestry	5.7
Fishing	29.0
Manufacturing (including, Mining, and Quarrying)	7.2
Electricity and Water	3.3
Construction	6.0
Wholesale and Retail Trade; Repair	9.5
Hotels and Restaurants	14.9
Transport and communication	11.1
Other Private Services (excluding FISIM 1)	2.6
Producers of Government Services	15.0
Taxes on Products	4.2

5.3 Comparison of Quarterly GDP Results

To compare the results of the current and previous nowcasting frameworks, the descriptive metrics RMSE and MAPE were used to compare predicted and actual GDP estimates for the period 2017Q1 and 2022Q1⁴.

Table 10: Comparison of Performance Metrics Between Previous and Current Nowcasting Frameworks

	Old Nowcasting Framework	New Nowcasting Framework
RMSE	47.2	30.7
MAPE	6.1	2.5

For Real GDP between 2017Q1-2022Q1, when the 11 and 16 sectoral models were aggregated to calculate respective RMSE and MAPE values, the new nowcasting framework outperformed the old in the two metrics employed. The RMSE improved by 35.0% between frameworks, while the MAPE was reduced by 3.6 percentage points from 6.1% to 2.5%, overall.

Table 11: Comparison of MAPE Between the Pre- and Post-Pandemic Era

	Old Nowcasting Framework	New Nowcasting Framework
MAPE: Pre-Pandemic Era	4.1	2.5
MAPE: Post-Pandemic Era	8.7	3.0

⁴ Despite estimates generated for 2017Q1 – 2022Q4 under the new framework, to compare like-to-like figures from the old framework, the sample was reduced to 2017Q1-2022Q1.

When comparing both models' MAPE performances in both the pre- and post-pandemic era, the new nowcasting framework significantly outperforms the old, as illustrated in Table 11 above. In the previous framework, the MAPE value more than doubled between the pre- and post-pandemic estimates from 4.1% to 8.7%, highlighting the model's inability to accurately respond to the multi-sectoral shock in 2020. However, in the new framework, the MAPE value remained relatively stable, increasing by 0.5 percentage points, representative of the mixed performances of the various sectoral models, yet highlighting the improved ability of the framework to account for the 2020 shock.

5.4 Major Takeaways

This paper's aim was twofold; enhance the Bank's GDP nowcasting framework to accurately capture the recent structural changes brought on by the 2022 rebasing exercise and to effectively capture the impact of economic shocks. To achieve this, the existing nowcasting framework was expanded to a total of 16 sectoral models utilising 45 indicators, inclusive of two dummy variables. As per the bottom-up approach, the estimates produced by the models were aggregated to arrive at a GDP estimate. Across the forecast period, the framework produced an accurate estimate of GDP, significantly bolstering the predictive power of the previous framework as proven by the RMSE and MAPE values tested. Nevertheless, critical observations were made regarding the complexity of maintaining the current number of models, as well as constraints brought on by the lack of timely indicators with sufficient explanatory power.

With all 16 sectoral models, estimating their respective GDP categories and performing at variable levels of accuracy, the likelihood for issues arising within a given model from quarter-to-quarter warrants pause. Evidence for this arose from the observation of varying MAPE levels for the models, which highlighted three models with higher-than-average levels of inaccuracy. Notably, the three worst performing models were tied to three of the smallest GDP categories in terms of their contribution to GDP. It was suggested in one study that the smaller components of GDP behave in a more volatile manner, driven by idiosyncratic forces (Dias, Pinhiero, & Rua, 2016). Alternatively, it is outlined in this paper that the weakness may stem from the explanatory variables chosen. Nevertheless, the models were kept in the framework despite their performance, as their contribution to the overall GDP estimate is insignificant.

Another pertinent downside to maintaining a high number of sectoral models, was a higher likelihood of the loss of predictive power by an indicator over a period of time. This can manifest particularly in any of the indices created with weights assigned to each indicator. This was surmised to be the case within the "*Professional and Administrative Services*" model, in which the BPO activity indicator grew in terms of its contribution to growth in the GDP category, diminishing the statistical importance of other indicators present in the index. This could be addressed in several ways, with the most likely outcome entailing the elimination of statistically insignificant variables within indices and/or the inclusion of new variables.

The complement of variables included in the nowcasting framework were found to accurately predict the movement of quarterly GDP except for a few that were either poorly correlated or did not provide sufficient causation. Nevertheless, multiple indicators presented structural breaks brought on by the pandemic. This was rectified within the models by the inclusion of two dummy variables capturing either the contraction, the rebound, or both, across 13 of the models following the pandemic, which allowed for improvements in model fitness. As a result, it was determined that the general accuracy of the sectoral models warranted their explicit inclusion and expansion, as they may be able to provide critical insight to policy makers monitoring targeted industries.

6.0 Conclusion

An accurate, reliable, and timely nowcasting estimator of quarterly GDP was deemed necessary to grasp the movements within the economy following the pandemic. This paper went a step further and reinforced the use of sectoral forecasts to provide policymakers with an added dimension of information to better inform their decisions. Altogether, despite the challenges in implementing a framework of this scale, the trade-off provided accurate estimates of not only quarterly GDP on a whole, but sectoral movements present within the various categories of GDP.

It is critical to note that similarly to the way in which this framework was born out of a need following the pandemic and revised to reflect the GDP rebasing exercise, further revisions will be necessary as Belize's economy matures. With the availability of a complement of sophisticated techniques aimed at estimating quarterly GDP, and the race towards producing results with the least amount of lag time, room exists to improve the framework considerably. As explored by Nakazawa (2022), non-traditional indicators may be implemented to supplement underperforming models ran, utilising less-than-ideal variables.

The decision to link the current framework to the statistical offices' production-based approach to calculating GDP prevented the inclusion of alternative data and restricted the number of variables utilised in this study. Thus, the impact of external variables such as the nation's leading trade partner's GDP growth, inflation, and price indices played no role in the generation of the current iteration of the framework.

A worthwhile effort would be the exploration and use of alternative variables simultaneously to generate a hybridised indicator list. This could prove to be a steppingstone to build a far more robust framework. It is only through adherence to the notion that the only constant in nowcasting is change, will more robust frameworks be produced.

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8.0 Appendix

Table A.1: Reclassification of Industrial Groupings

Base Year 2000	Base Year 2014	Notes
Agriculture, Hunting and Forestry	Agriculture, Forestry and Fishing	Absorbed "Fishing"
Fishing	Mining	Disaggregated from "Manufacturing"
Manufacturing (including Mining and Quarrying)	Manufacturing	
	Electricity	Disaggregated from "Electricity and Water"
Electricity and Water	Water Supply	Disaggregated from "Electricity and Water"
Construction	Construction	
Wholesale and Retail Trade; Repair	Wholesale and Retail Trade	
Hotels and Restaurants	Accommodation and Food Service Activities	
Transport and Communication	Transportation	Disaggregated from "Transport and Communication"
	Information and Communication	Disaggregated from "Transport and Communication"
	Financial and Insurance Activities	Disaggregated from "Other Private Services"
	Real Estate Activities	Disaggregated from "Other Private Services"
	Professional Scientific and Technical Activities	Disaggregated from "Other Private Services"
Other Private Services excluding (FISIM 1)	Administrative and Support Service Activities	Disaggregated from "Other Private Services"
	Arts, Entertainment, Recreation	Disaggregated from "Other Private Services"
	Other Service Activities	Disaggregated from "Other Private Services"
	Activities of Households as Employers	Disaggregated from "Other Private Services"
	Public Administration and Defence	Disaggregated from "Producers of Government Services"
Producers of Government Services	Education	Disaggregated from "Producers of Government Services"
	Human Health and Social Work Activities	Disaggregated from "Producers of Government Services"
Taxes on Products	Taxes and Subsidies	

Table A.2: Indicator and Index Component List

Sector	Index	Indicator	Frequency
Primary	Agricultural Index	Grapefruit Deliveries	Monthly
		Orange Deliveries	Monthly
		Banana Production	Monthly
		Sugarcane Production	Monthly
		Other Crops	Quarterly
		Chicken	Quarterly
		Beef	Quarterly
		Conch	Monthly
		Farmed Shrimp	Monthly
		Fish	Monthly
		Lobster	Monthly
		Oil Production Value	Monthly
Secondary	Manufacturing Index	Beer	Quarterly
		Flour	Quarterly
		Soft Drinks	Quarterly
		ONFC	Monthly
		GNFC	Monthly
		Grapefruit Concentrates	Monthly
		Orange Concentrates	Monthly
		Animal Feed	Monthly
		Fertilizer	Quarterly
		Dairy Production	Quarterly
		Sugar Production	Monthly
		Electricity Production	Monthly
		Water Distribution	Monthly
		Cement Imports	Quarterly
		Loans for Construction	Monthly
Tertiary and Taxes	Tourist Arrival Index	Air Arrivals	Monthly
		Sea Arrivals	Monthly
		Cruise Arrivals	Monthly
		Land Arrivals	Monthly
	Transportation Index	Sugar Production	Monthly
		Total Tourist Arrivals	Monthly
		Gross Merchandise Imports	Monthly
	Professional and Administrative Services Index	Business Tax	Monthly
		Business Processing and Outsourcing Income	Monthly
		General Sales Tax Collections	Monthly
		Government Current Expenditure	Monthly
		Government Wages and Salaries	Monthly
		Government Current Revenue	Monthly
		Total Loans	Monthly
		Money Supply	Monthly
		Saria	Monthly
		Gross Merchandise Imports	Monthly
		Total Tourist Arrivals	Monthly
		General Sales Tax Collections	Monthly

Table A.3: Agriculture Sectoral Model Results

Dependent Variable: D(LAGDP)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/23/25 Time: 14:36
Sample: 2000Q1 2022Q4
Included observations: 92
Convergence achieved after 8 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LAGDP(-2))	-0.957417	0.015964	-59.97285	0.0000
D(LAG)	0.260063	0.087885	2.959118	0.0040
D(LAG(-2))	0.180614	0.051598	3.500427	0.0007
AR(2)	0.677062	0.059673	11.34612	0.0000
MA(2)	0.571109	0.111837	5.106608	0.0000
SIGMASQ	0.052209	0.005624	9.283798	0.0000
R-squared	0.809572	Mean dependent var		0.007376
Adjusted R-squared	0.798500	S.D. dependent var		0.526476
S.E. of regression	0.236328	Akaike info criterion		0.051932
Sum squared resid	4.803196	Schwarz criterion		0.216396
Log likelihood	3.611143	Hannan-Quinn criter.		0.118311
Durbin-Watson stat	2.665985			
Inverted AR Roots	.82	-.82		
Inverted MA Roots	-.00+.76i	-.00-.76i		

Table A.4: Mining Sectoral Model Results

Dependent Variable: D(LMNGDP)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/23/25 Time: 11:48
Sample: 2016Q2 2022Q4
Included observations: 27
Convergence achieved after 12 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LOILVALUE)	0.437011	0.159410	2.741422	0.0114
MA(1)	-0.813823	0.174622	-4.660474	0.0001
SIGMASQ	0.049802	0.012571	3.961604	0.0006
R-squared	0.185561	Mean dependent var		-0.017352
Adjusted R-squared	0.117691	S.D. dependent var		0.251993
S.E. of regression	0.236700	Akaike info criterion		0.100603
Sum squared resid	1.344648	Schwarz criterion		0.244585
Log likelihood	1.641862	Hannan-Quinn criter.		0.143416
Durbin-Watson stat	0.774130			
Inverted MA Roots	.81			

Table A.5: Manufacturing Sectoral Model Results

Dependent Variable: D(LMGDP)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/23/25 Time: 11:48
Sample: 2000Q1 2022Q4
Included observations: 92
Convergence achieved after 15 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(2)	-0.993319	0.003880	-256.0212	0.0000
MA(2)	0.537107	0.083326	6.445822	0.0000
SIGMASQ	0.019403	0.003485	5.567921	0.0000
R-squared	0.909778	Mean dependent var		0.007273
Adjusted R-squared	0.907751	S.D. dependent var		0.466289
S.E. of regression	0.141624	Akaike info criterion		-0.971092
Sum squared resid	1.785099	Schwarz criterion		-0.888860
Log likelihood	47.67024	Hannan-Quinn criter.		-0.937902
Durbin-Watson stat	2.953667			
Inverted AR Roots	-.00+1.00i	-.00-1.00i		
Inverted MA Roots	-.00+.73i	-.00-.73i		

Table A.6: Electricity Sectoral Model Results

Dependent Variable: D(LEW)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/23/25 Time: 11:48
Sample: 2000Q2 2022Q4
Included observations: 91
Convergence achieved after 9 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LE)	0.979880	0.040833	23.99725	0.0000
COVIDDUMMY20	0.042261	0.905283	0.046683	0.9629
AR(2)	0.162963	0.080724	2.018778	0.0466
MA(1)	0.838484	0.094452	8.877328	0.0000
SIGMASQ	0.012417	0.000747	16.61883	0.0000
R-squared	0.913655	Mean dependent var		0.011263
Adjusted R-squared	0.909639	S.D. dependent var		0.381316
S.E. of regression	0.114624	Akaike info criterion		-1.429675
Sum squared resid	1.129932	Schwarz criterion		-1.291716
Log likelihood	70.05022	Hannan-Quinn criter.		-1.374017
Durbin-Watson stat	1.244513			
Inverted AR Roots	.40	-.40		
Inverted MA Roots	-.84			

Table A.7: Water Supply Sectoral Model Results

Dependent Variable: D(LWGDP)

Method: ARMA Maximum Likelihood (BFGS)

Date: 01/23/25 Time: 11:48

Sample: 2000Q1 2022Q4

Included observations: 92

Convergence achieved after 4 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LWGDP(-2))	-0.886236	0.053204	-16.65744	0.0000
LWATERSUP	0.002249	0.000922	2.438512	0.0168
COVIDDUMMY20	-0.056594	0.042635	-1.327389	0.1879
COVIDDUMMY21	-0.005001	0.031498	-0.158776	0.8742
AR(2)	0.497993	0.105932	4.701067	0.0000
SIGMASQ	0.001349	0.000214	6.314172	0.0000
R-squared	0.611911	Mean dependent var		0.008487
Adjusted R-squared	0.589348	S.D. dependent var		0.059274
S.E. of regression	0.037984	Akaike info criterion		-3.634126
Sum squared resid	0.124078	Schwarz criterion		-3.469662
Log likelihood	173.1698	Hannan-Quinn criter.		-3.567747
Durbin-Watson stat	2.073039			
Inverted AR Roots	.71	-.71		

Table A.8: Construction Sectoral Model Results

Dependent Variable: D(LCGDP)

Method: ARMA Maximum Likelihood (BFGS)

Date: 01/23/25 Time: 11:48

Sample: 2008Q2 2022Q4

Included observations: 59

Convergence achieved after 4 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LISUPNES)	0.279319	0.091815	3.042181	0.0036
COVID	-0.008246	0.028472	-0.289620	0.7732
AR(8)	0.314001	0.153009	2.052177	0.0449
SIGMASQ	0.008510	0.001401	6.074883	0.0000
R-squared	0.168835	Mean dependent var		0.003743
Adjusted R-squared	0.123499	S.D. dependent var		0.102055
S.E. of regression	0.095546	Akaike info criterion		-1.778964
Sum squared resid	0.502092	Schwarz criterion		-1.638114
Log likelihood	56.47945	Hannan-Quinn criter.		-1.723982
Durbin-Watson stat	1.893635			
Inverted AR Roots	.87	.61-.61i	.61+.61i	-.00-.87i
	-.00+.87i	-.61+.61i	-.61+.61i	-.87

Table A.9: Wholesale and Retail Trade Sectoral Model Results

Dependent Variable: D(LWR)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/23/25 Time: 11:48
Sample: 2000Q2 2022Q4
Included observations: 91
Convergence achieved after 5 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LWR(-1))	-0.251061	0.073810	-3.401471	0.0010
D(LTOUR)	0.026066	0.008748	2.979781	0.0038
D(LM)	0.354483	0.041138	8.617007	0.0000
D(LGTAX)	0.101250	0.053152	1.904892	0.0603
COVID	0.003761	0.009900	0.379923	0.7050
AR(4)	0.322154	0.121497	2.651533	0.0096
MA(1)	-0.276300	0.123095	-2.244603	0.0275
SIGMASQ	0.000985	0.000160	6.149340	0.0000
R-squared	0.798565	Mean dependent var		0.006705
Adjusted R-squared	0.781576	S.D. dependent var		0.070330
S.E. of regression	0.032869	Akaike info criterion		-3.903102
Sum squared resid	0.089672	Schwarz criterion		-3.682367
Log likelihood	185.5911	Hannan-Quinn criter.		-3.814049
Durbin-Watson stat	1.781848			
Inverted AR Roots	.75	-.00+.75i	-.00-.75i	-.75
Inverted MA Roots	.28			

Table A.10: Hotels and Restaurant Activities Sectoral Model Results

Dependent Variable: D(LHR)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/23/25 Time: 11:48
Sample: 2000Q2 2022Q4
Included observations: 91
Convergence achieved after 20 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LTOUR)	1.011395	0.019854	50.94119	0.0000
COVIDDUMMY20(2)	0.099296	0.070730	1.403875	0.1640
AR(2)	-0.977235	0.035267	-27.70944	0.0000
MA(2)	0.894938	0.099618	8.983709	0.0000
SIGMASQ	0.004656	0.000425	10.94714	0.0000
R-squared	0.986596	Mean dependent var		0.000498
Adjusted R-squared	0.985973	S.D. dependent var		0.592636
S.E. of regression	0.070190	Akaike info criterion		-2.409464
Sum squared resid	0.423694	Schwarz criterion		-2.271504
Log likelihood	114.6306	Hannan-Quinn criter.		-2.353806
Durbin-Watson stat	2.033262			
Inverted AR Roots	-.00+.99i	-.00-.99i		
Inverted MA Roots	-.00+.95i	-.00-.95i		

Table A.11: Transportation Sectoral Model Results

Dependent Variable: D(LTGDP)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/23/25 Time: 11:48
Sample: 2000Q1 2022Q4
Included observations: 92
Convergence achieved after 18 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LTGDP(-1))	-0.285446	0.039968	-7.141913	0.0000
D(LTGDP(-3))	-0.379723	0.046877	-8.100392	0.0000
D(LGTAX)	0.181454	0.065055	2.789212	0.0066
D(LTRAN)	0.579456	0.040728	14.22750	0.0000
D(LM)	0.127852	0.065417	1.954405	0.0541
D(LM(-2))	-0.280217	0.056533	-4.956707	0.0000
D(LAR)	-0.075923	0.017069	-4.448056	0.0000
AR(1)	-0.627151	0.258206	-2.428879	0.0173
MA(1)	0.813046	0.191392	4.248067	0.0001
SIGMASQ	0.004191	0.000657	6.379533	0.0000
R-squared	0.879385	Mean dependent var		0.007695
Adjusted R-squared	0.866147	S.D. dependent var		0.187420
S.E. of regression	0.068569	Akaike info criterion		-2.417928
Sum squared resid	0.385545	Schwarz criterion		-2.143821
Log likelihood	121.2247	Hannan-Quinn criter.		-2.307296
Durbin-Watson stat	1.971325			
Inverted AR Roots	-.63			
Inverted MA Roots	-.81			

Table A.12: Financial Activities Sectoral Model Results

Dependent Variable: D(LOPS)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/23/25 Time: 11:48
Sample: 2000Q1 2022Q4
Included observations: 92
Convergence achieved after 5 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LM2)	0.017598	0.002536	6.938413	0.0000
COVID	0.003273	0.011414	0.286779	0.7750
LDEP	0.008798	0.001962	4.483737	0.0000
LPROFADMIN	-0.006125	0.001794	-3.414911	0.0010
AR(6)	-0.271475	0.141426	-1.919562	0.0583
MA(1)	0.631339	0.119635	5.277203	0.0000
SIGMASQ	0.000495	6.84E-05	7.227406	0.0000
R-squared	0.584432	Mean dependent var		0.015592
Adjusted R-squared	0.555098	S.D. dependent var		0.034690
S.E. of regression	0.023139	Akaike info criterion		-4.610682
Sum squared resid	0.045509	Schwarz criterion		-4.418807
Log likelihood	219.0914	Hannan-Quinn criter.		-4.533240
Durbin-Watson stat	1.753621			
Inverted AR Roots	.70+.40i	.70-.40i	.00-.80i	-.00+.80i
	-.70+.40i	-.70-.40i		
Inverted MA Roots	-.63			

Table A.13: : Real Estate Activities Sectoral Model Results

Dependent Variable: D(LRGDP)

Method: ARMA Maximum Likelihood (BFGS)

Date: 01/23/25 Time: 11:48

Sample: 2000Q1 2022Q4

Included observations: 92

Convergence achieved after 5 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LRGDP(-1))	0.606598	0.082181	7.381207	0.0000
D(LRGDP(-2))	-0.305026	0.084141	-3.625164	0.0005
D(LHOUSCPI(1))	0.066783	0.038047	1.755271	0.0829
C	0.002973	0.000735	4.042421	0.0001
COVID	-0.001853	0.002312	-0.801375	0.4252
AR(4)	-0.399633	0.114531	-3.489315	0.0008
MA(6)	0.612908	0.115492	5.306954	0.0000
SIGMASQ	1.41E-05	2.44E-06	5.785851	0.0000
R-squared	0.530415	Mean dependent var		0.004335
Adjusted R-squared	0.491283	S.D. dependent var		0.005510
S.E. of regression	0.003930	Akaike info criterion		-8.118118
Sum squared resid	0.001297	Schwarz criterion		-7.898832
Log likelihood	381.4334	Hannan-Quinn criter.		-8.029612
F-statistic	13.55447	Durbin-Watson stat		1.879108
Prob(F-statistic)	0.000000			
Inverted AR Roots	.56-.56i	.56-.56i	-.56+.56i	-.56+.56i
Inverted MA Roots	.80+.46i	.80-.46i	-.00+.92i	-.00-.92i
	-.80-.46i	-.80+.46i		

Table A.14: : Professional and Administrative Activities Sectoral Model Results

Dependent Variable: D(LPGDP)

Method: ARMA Maximum Likelihood (BFGS)

Date: 01/23/25 Time: 11:48

Sample: 2000Q3 2022Q4

Included observations: 90

Convergence achieved after 7 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LPROFADMIN)	-0.507803	0.107345	-4.730579	0.0000
D(LPROFADMIN(-1))	0.611125	0.112672	5.423950	0.0000
COVIDDUMMY20	0.033136	0.036308	0.912638	0.3641
D(LAR)	0.195438	0.030595	6.387826	0.0000
D(LAR(-1))	-0.194533	0.027617	-7.043960	0.0000
AR(3)	-0.335579	0.109793	-3.056464	0.0030
MA(1)	-0.664597	0.093261	-7.126238	0.0000
SIGMASQ	0.010886	0.001906	5.711173	0.0000
R-squared	0.681096	Mean dependent var		0.012398
Adjusted R-squared	0.653872	S.D. dependent var		0.185798
S.E. of regression	0.109310	Akaike info criterion		-1.492032
Sum squared resid	0.979784	Schwarz criterion		-1.269826
Log likelihood	75.14142	Hannan-Quinn criter.		-1.402425
Durbin-Watson stat	1.903085			
Inverted AR Roots	.35+.60i	.35-.60i	-.69	
Inverted MA Roots	.66			

Table A.15: Public Admin. And Defence Activities Sectoral Model Results

Dependent Variable: D(LGGDP)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/23/25 Time: 11:48
Sample: 2000Q1 2022Q4
Included observations: 92
Convergence achieved after 7 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LGGDP(-1))	-0.466679	0.087451	-5.336454	0.0000
D(LGGDP(-2))	-0.385494	0.100651	-3.830019	0.0002
D(LGGDP(-3))	-0.413361	0.100691	-4.105228	0.0001
COIDDUMMY20	-0.214200	0.039130	-5.474071	0.0000
COIDDUMMY21	0.122336	0.026621	4.595439	0.0000
C	0.018528	0.003375	5.489331	0.0000
MA(4)	-0.451867	0.114269	-3.954415	0.0002
SIGMASQ	0.001923	0.000306	6.291175	0.0000
R-squared	0.404959	Mean dependent var		0.006825
Adjusted R-squared	0.355373	S.D. dependent var		0.057161
S.E. of regression	0.045893	Akaike info criterion		-3.232117
Sum squared resid	0.176922	Schwarz criterion		-3.012831
Log likelihood	156.6774	Hannan-Quinn criter.		-3.143611
F-statistic	8.166693	Durbin-Watson stat		2.069976
Prob(F-statistic)	0.000000			
Inverted MA Roots	.82	.00-.82i	.00+.82i	-.82

Table A.16: Education and Health Activities Sectoral Model Results

Dependent Variable: D(LEHGDP)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/23/25 Time: 11:48
Sample: 2000Q1 2022Q4
Included observations: 92
Convergence achieved after 3 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LEHGDP(-1))	-0.997954	0.006543	-152.5337	0.0000
D(LEHGDP(-2))	-0.995685	0.008849	-112.5250	0.0000
D(LEHGDP(-3))	-0.994152	0.004424	-224.7038	0.0000
AR(1)	0.497574	0.078982	6.299839	0.0000
SIGMASQ	0.001118	0.000126	8.901999	0.0000
R-squared	0.997677	Mean dependent var		0.003568
Adjusted R-squared	0.997570	S.D. dependent var		0.697626
S.E. of regression	0.034387	Akaike info criterion		-3.846384
Sum squared resid	0.102873	Schwarz criterion		-3.709331
Log likelihood	181.9337	Hannan-Quinn criter.		-3.791068
Durbin-Watson stat	2.023341			
Inverted AR Roots	.50			

Table A.17: Other Service Activities Sectoral Model Results

Dependent Variable: D(LOGDP)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/23/25 Time: 11:48
Sample: 2000Q2 2022Q4
Included observations: 91
Convergence achieved after 8 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LTOUR)	0.076189	0.016196	4.704254	0.0000
MA(1)	-0.773286	0.077393	-9.991717	0.0000
SIGMASQ	0.012172	0.002921	4.167142	0.0001
R-squared	0.324461	Mean dependent var		0.004424
Adjusted R-squared	0.309108	S.D. dependent var		0.134975
S.E. of regression	0.112191	Akaike info criterion		-1.494808
Sum squared resid	1.107635	Schwarz criterion		-1.412032
Log likelihood	71.01375	Hannan-Quinn criter.		-1.461413
Durbin-Watson stat	1.655286			
Inverted MA Roots	.77			

Table A.18: Taxes and Subsidies Sectoral Model Results

Dependent Variable: D(LTAX)
Method: Least Squares
Date: 01/23/25 Time: 11:48
Sample: 2000Q1 2022Q4
Included observations: 92

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LM)	0.466131	0.041244	11.30189	0.0000
D(LGTAX)	0.176653	0.049346	3.579889	0.0006
COVIDDUMMY21	0.015778	0.024035	0.656462	0.5132
R-squared	0.654893	Mean dependent var		0.012121
Adjusted R-squared	0.647138	S.D. dependent var		0.078999
S.E. of regression	0.046927	Akaike info criterion		-3.248367
Sum squared resid	0.195994	Schwarz criterion		-3.166135
Log likelihood	152.4249	Hannan-Quinn criter.		-3.215178
Durbin-Watson stat	2.197745			

