INTERNATIONAL MONETARY FUND

Nowcasting Real GDP in Samoa

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WP/25/92

2025
MAY

WORKING PAPER

 WP/25/92

IMF Working Paper
Institute for Capacity Development

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Authorized for distribution by Natan Epstein
May 2025

ABSTRACT: This paper describes the recent work to strengthen the nowcasting capacity at the Central Bank of Samoa (CBS). It compiles available high-frequency datasets such as tourism receipts, agriculture market survey, remittances, among others, to nowcast real GDP in Samoa. Nowcasting enables the estimation of the present and near-term forecast. It employs standard nowcasting methods such as Bridge, Mixed Data Sampling (MIDAS), and Unrestricted MIDAS (U-MIDAS). All methods significantly outperform the naive forecasts. Our analysis show that forecast combination of the three methods minimizes the root mean squared error (RMSE) for both full and pre-COVID-19 samples, while U-MIDAS performs better during crises, particularly in identifying turning points during the COVID-19 pandemic. Strengthening nowcasting capacity is important for Samoa, where real GDP data release experiences up to a 90-day lag.

JEL Classification Numbers:	E17, C53
Keywords:	Forecasting; Nowcasting; Real GDP; Samoa
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WORKING PAPERS

Nowcasting Real GDP in Samoa

Prepared by Geoffrey Michael Heenan, Karras Lui, Ian Nield, Eucharist Muaulu, Viiaonaoperesi Reupena, Ivy Sabuga, and Aiulu Tolovaa[1]

[1] IMF Institute for Capacity Development (ICD) technical assistance and bespoke training missions, which led to the development of this tool, were provided to the Central Bank of Samoa (CBS) under ICD's Macroeconomic Frameworks TA project. This paper greatly benefited from discussions with staff of the CBS and the IMF Asia-Pacific Department. We are grateful for comments from Mr. Paul Cashin, Ms. Margaret Chan Cheuk-Tafunai, and Diaa Noureldin. The Macroeconomic Frameworks TA to Samoa was supported by the Government of Japan. The views expressed in this paper are those of the authors and not necessarily those of the CBS authorities, the International Monetary Fund, or its Executive Board.

Contents

Glossary

ADF	Augmented Dicky-Fuller
AIC	Akaike Information Criteria
CBS	Central Bank of Samoa
COVID-19	Corona Virus Disease
DFMs	Dynamic Factor Models
FPAS	Forecasting and Policy Analysis System
GDP	Gross Domestic Product
ICD	Institute for Capacity Development
IMF	International Monetary Fund
LICs	Low-Income Countries
MIDAS	Mixed Data Sampling
MCR	Ministry of Customs and Revenue
NOAA	National Oceanic and Atmospheric Administration
OLS	Ordinary Least Squares
OMO	Open Market Operations
PICs	Pacific Island Countries
PSL	Physical Science Laboratory
RMSE	Root Mean Squared Error
TA	Technical Assistance
SBS	Samoa Bureau of Statistics
U-MIDAS	Unrestricted- Mixed Data Sampling
VAR	Vector Autoregression

I. Introduction

The considerable lag in the dissemination of Samoan official statistics has underscored the necessity of developing a nowcasting framework to estimate Samoa's real gross domestic product (GDP) in a timely manner. GDP growth, due to its comprehensive scope, is a key indicator for guiding the policymaking process. However, it is important to acknowledge that the availability of GDP data markedly differs across nations, influencing the promptness of economic assessments and decision-making processes. Specifically, in Samoa, GDP figures are released roughly 90 days, or three months, following the end of a reference quarter. Such lags in data release, although typical of many economies, hinder the ability to conduct real-time economic analysis and formulate policy, particularly in swiftly evolving economic contexts. This scenario emphasizes the critical need for nowcasting methods capable of delivering accurate and prompt economic trend predictions, even in the absence of the latest data. Samoa's experience with delayed GDP data release is a common issue of data timeliness and completeness, affecting many low-income countries (LICs) and emerging market economies (EMEs).

Nowcasting, a method that relies on readily, timely available data to forecast real GDP before the official statistics are released, is well-suited to this context. Given the notable lags in publishing official real GDP figures, a variety of high-frequency economic indicators act as a crucial link throughout the forecast period in Samoa. These high-frequency data encompass a wide array of variables, including, but not limited to, tourism statistics, remittances, agricultural production market surveys, external sector indicators, fiscal, financial, and monetary variables, and an El Niño indicator.[1] Utilizing nowcasting techniques allows policymakers and analysts to acquire a more immediate grasp of the economic landscape through providing additional inputs to macroeconomic surveillance and so facilitating a more timely and well-informed decision-making process.

Following a request by the Central Bank of Samoa (CBS) in 2022, the IMF's Institute for Capacity Development (ICD) initiated a targeted Macroeconomic Framework technical assistance (TA) program.[2] The objective of this program is to strengthen the CBS's capabilities in analysis and policy formulation, utilizing the Forecasting and Policy Analysis System (FPAS) macroeconomic framework. In undertaking this work, ICD collaborated with the CBS to develop a nowcasting tool aimed at estimating Samoa's real GDP. This important analytical tool has been seamlessly incorporated into the CBS' standard policy analysis routine, thus incorporating a tool that can estimate real GDP growth up to three months before the official statistics are released. The results are summarized in a one-page document, detailing the impact of the indicators on the projected real GDP growth. This methodology assists policymakers to form an up-to-date economic narrative, ensuring they have a comprehensive understanding of the prevailing economic conditions. This methodology helps policy makers obtain a comprehensive understanding of the prevailing economic conditions and form an up-to-date economic narrative.

This paper describes this recent work to develop the CBS' nowcasting capacity. The structure of the remainder of this document is as follows: Section 2 introduces key stylized facts about Samoa's economy, with a particular emphasis on the factors driving its GDP growth. Section 3 outlines the methodology used to

[1] See Table 2 for the complete list of indicators.

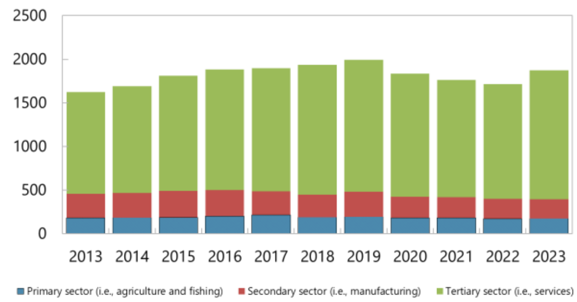
[2] This Macroeconomic Framework TA program is similar to other ongoing programs in Asia-Pacific region, such as those in Cambodia (see Heng et al., 2024) and Tonga (see Ouliaris et al., 2025).

construct a nowcasting framework specifically for Samoa, and presents three benchmark nowcasting methods employed to estimate Samoa's current and next quarter real GDP, including an analysis of their performance and an evaluation of their effectiveness. The paper concludes with Section 4.

II. Samoa's Economy and GDP – Stylized Facts

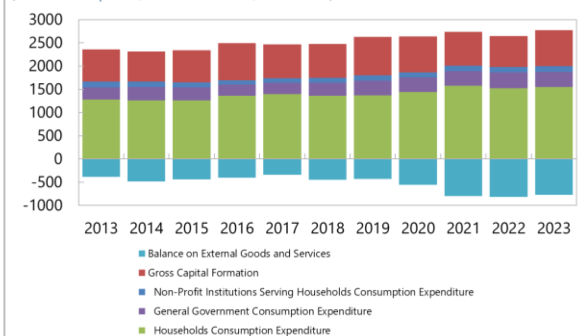
Samoa's economy is dominated by the services sector on the production side and household consumption on the expenditure side. The compilation and dissemination of GDP data in Samoa utilize both the expenditure and production approaches. Under the production approach, the economy is dominated by the services sector (80% of GDP), with manufacturing and agriculture & fisheries comprising approximately 10% each (see Figure 1). From the expenditure perspective, the backbone of Samoa's economy is household consumption, accounting for about 80% of GDP. Government consumption further contributes around 20%, while capital formation makes up approximately 40% of GDP, being balanced by net exports of goods and services which represents about -40% of GDP (see Figure 2).

Figure 1. GDP by Industry, Fiscal Year
(At constant prices, in millions WST, 2013=100)



Note: Samoa's GDP is computed using fiscal year from July-June.
Sources: Samoa Bureau of Statistics and IMF staff calculations

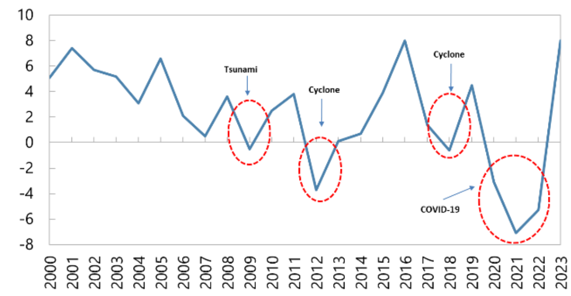
Figure 2. GDP by Expenditure, Fiscal Year
(At constant prices, in millions WST, 2013=100)



Note: Samoa's GDP is computed using fiscal year from July-June.
Sources: Samoa Bureau of Statistics and IMF staff calculations

Samoa's economic growth is vulnerable to the threats of natural disasters and climate-related hazards. The nation's economy faces threats from its susceptibility to climate-related hazards, such as tropical cyclones, earthquakes, tsunamis, droughts, and floods (heavily influenced by El Niño conditions), which can significantly undermine economic performance (as highlighted in Figure 3). Meanwhile, following its recovery from a measles outbreak in November 2019, Samoa encountered the onset of the COVID-19 pandemic. The COVID-19 pandemic resulted in a significant economic contraction, especially in the tourism and services sectors. These consecutive health emergencies plunged Samoa into a three-year economic downturn, with negative economic growth rates from 2020-2022 (see IMF (2023) Samoa Article IV Country Report; CBS (2023) Annual Report).

Figure 3. GDP Growth, Fiscal Year
(At constant prices, annual percent change)

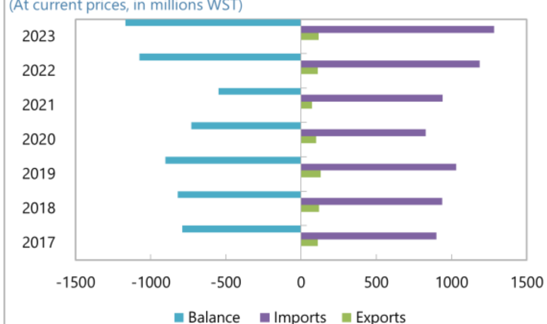


Note: Samoa's GDP is computed using fiscal years July-June.
Sources: Samoa Bureau of Statistics (SBS) and IMF WEO Database.

Following the reopening of international borders in August 2022, Samoa began to recover economically, with increased activity in several sectors. This resurgence was largely driven by a robust recovery in tourism, an increase in remittances, and elevated public investment. Samoa's economy is mostly dependent on remittances that supports household consumption, and tourism that drives a significant part of its services sector.[3]

Samoa's is a net importer of goods, significantly relying on imports from Singapore and New Zealand. In terms of trade, Samoa primarily imports from Singapore (notably mineral fuels) and New Zealand (mainly food products) as shown in Figure 5. Conversely, American Samoa and New Zealand emerge as the leading destinations for Samoan exports, as illustrated in Figure 6.

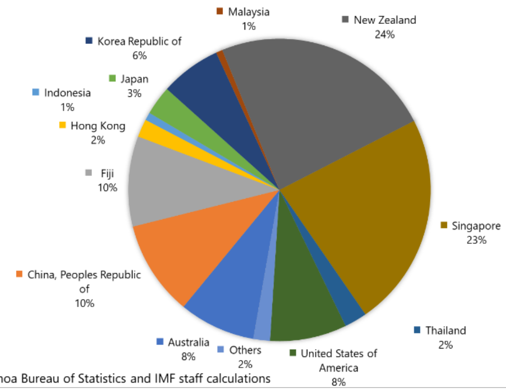
Figure 4. Merchandise Trade, Calendar Year
(At current prices, in millions WST)



Sources: Samoa Bureau of Statistics and IMF staff calculations

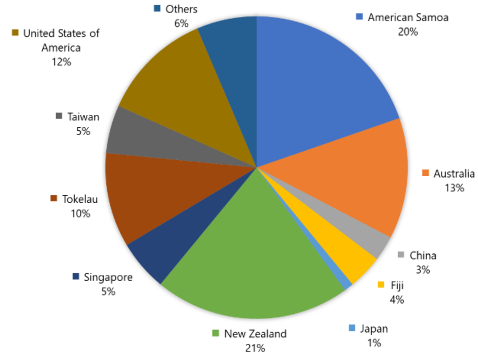
[3] Remittances are approximately 45 percent of household consumption expenditure while tourism is around 30 percent of GDP (IMF (2023); CBS (2023)).

Figure 5. Total Merchandise Imports
(2023 calendar year, source by country, percent share of total)



Sources: Samoa Bureau of Statistics and IMF staff calculations

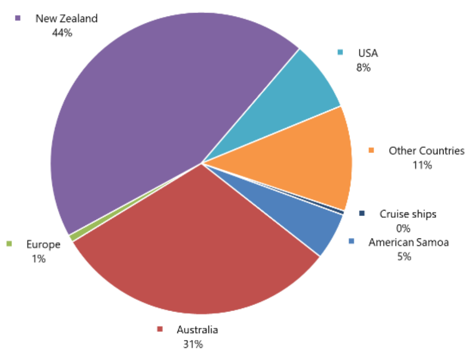
Figure 6. Total Merchandise Exports
(2023 calendar year, destination by country, percent share of total)



Sources: Samoa Bureau of Statistics and IMF staff calculations

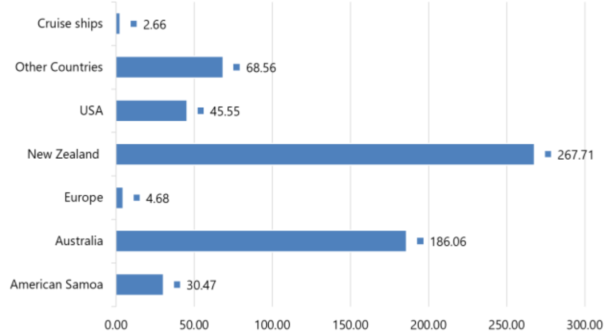
New Zealand and Australia stand as Samoa's largest contributors to tourism revenue. Based on 2023 data, New Zealand and Australia accounted for approximately 44 percent and 31 percent, respectively, of Samoa's total tourism earnings (Figures 7 and 8).

Figure 7. Total Tourism Earnings
(2023 calendar year, source by country, percent share of total)



Sources: Central Bank of Samoa and IMF staff calculations

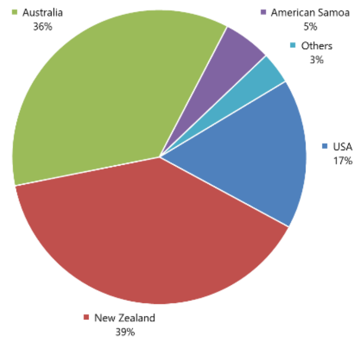
Figure 8. Total Tourism Earnings
(2023 calendar year, source by country, in millions WST)



Sources: Central Bank of Samoa and IMF staff calculations

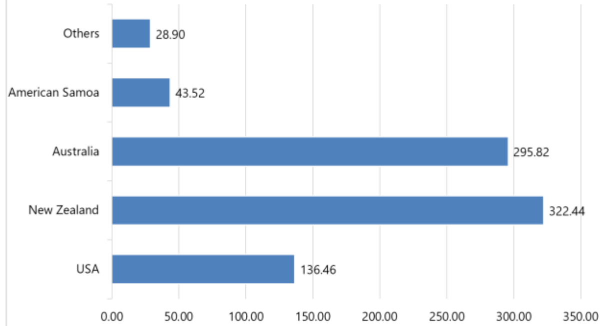
New Zealand and Australia are also the leading sources of remittances for Samoa. New Zealand and Australia share in 2023 are around 39 percent and 36 percent, respectively (Figure 9 and 10).

Figure 9. Inflow of Private Remittances
(2023 calendar year, source by country, percent share of total)



Sources: Central Bank of Samoa and IMF staff calculations

Figure 10. Inflow of Private Remittances
(2023 calendar year, source by country, in millions WST)



Sources: Central Bank of Samoa and IMF staff calculations

The CBS operates its monetary policy primarily through the issuance of its securities via open market operations (OMO). These CBS securities are the main tool for monetary policy, aimed at altering liquidity levels within the financial system. Through OMO, the CBS methodically affects the availability of free liquidity and, as a result, the interest rate landscape within Samoa's financial market. The primary goal of these operations is centered on reserve money, especially targeting the free liquidity of commercial banks, as reflected in the total balance of the commercial banks' exchange settlement accounts or their demand deposits at the CBS. Currently, to address and stabilize the high liquidity levels in the financial system, the CBS persists in its policy efforts, issuing securities to soak up the excess liquidity (see IMF (2023; 2024); CBS (2023)).

III. Nowcasting Real GDP for Samoa

Despite Samoa releasing its GDP data quarterly, which is more frequent than many other Pacific Island Countries (PICs) and LICs more generally, it still encounters modest lags, with data being published 90 days after the end of each quarter. This delay underscores the priority for the availability and use of a nowcasting model for Samoa, which employs early available indicators (e.g., monthly) to forecast real GDP before the official figures are released. In developing a nowcasting tool for Samoa, we gather all available information that might indicate the direction of Samoa's GDP, in a fashion similar to leading GDP indicators.

The creation of a nowcasting tool for the CBS to estimate Samoa's real GDP involved several key stages. These phases were (i) selecting predictors by identifying main economic variables that can forecast real GDP effectively; (ii) evaluating and choosing the model through econometric techniques to find the most suitable one; (iii) conducting in-sample nowcasting exercises to test the model's forecasting ability over time (backtesting); and (iv) documenting the nowcasting process, which will serve as training materials available for future reference. The four phases were repeated several times before resulting in an acceptable model. This repetitive process helped to instill an appreciation of the need to continually improve the precision of the nowcasting models, which may include refining the model by adding new variables as they become available.

The process of choosing indicators to nowcast Samoa's real GDP involved a careful balance between data availability and quality. In selecting predictors to nowcast real GDP, we began by including all accessible high-frequency indicators that could inform the dynamics of Samoa's real GDP. A detailed list of these indicators is provided in Table 1.[4] Throughout this selection process, we were mindful of the trade-offs involved in including certain variables, especially those with sparse historical data.

Table 1. Pre-Selected Indicators to Nowcast Samoa's Real GDP

Series Name	Description	Start	End	Source
rgdp	Samoa: Real GDP	2000:Q1	2022:Q3	Samoa Bureau of Statistics (SBS)
aus_pmi	Australia: PMI† (SA, 50+=Expansion)	2002:M08	2023:M03	Haver
nz_pmi	New Zealand: PMI (SA, 50+=Expansion)	2002:M08	2023:M03	Haver
remitt	Samoa: Total remittances (in millions WST)	1993:M01	2023:M03	CBS
for_res_usd	Samoa: Foreign reserves (in millions USD)	2000:M01	2023:M03	CBS
for_res_wst	Samoa: Foreign reserves (in millions WST)	2000:M01	2023:M03	CBS
bank_credit_m	Samoa: Commercial banks' total credit to private sector and public institutions (in millions WST)	1999:M01	2023:M03	CBS
m2	Samoa: Broad money	2001:M01	2023:M03	CBS
curr_cir	Samoa: Currency in circulation	2001:M01	2023:M03	CBS
cob	Samoa: Currency outside banks	2001:M01	2023:M03	CBS
cpi	Samoa: Consumer price index	1967:M01	2023:M03	CBS
ex_rate	Samoa: Exchange rate (WST/USD)	2005:M07	2023:M03	CBS
tour_rec	Samoa: Tourist receipts (in millions WST)	2002:M08	2023:M03	CBS
tour_arrival	Samoa: Total tourist arrivals (persons)	2002:M08	2023:M03	CBS
tour_exp	Samoa: Average tourist expenditure (WST, per person)	2002:M08	2023:M03	CBS
agri_prod	Samoa: Agricultural production	2000:Q1	2022:Q3	SBS
mark_svey_val	Samoa: Fugalei market survey‡ (index)	1993:M01	2023:M03	SBS
mark_svey_vol	Samoa: Fugalei market survey volume	1993:M01	2023:M03	SBS
mark_svey_price	Samoa: Fugalei market survey prices	1993:M01	2023:M03	SBS
imp	Total merchandise imports (in millions WST)	2000:M01	2023:M03	CBS
exp	Samoa: Total merchandise exports (in million WST)	2000:M01	2023:M03	CBS
covid_gfc	Samoa: Dummy variable to capture structural breaks due to the Global Financial Crisis (GFC) and COVID-19	2003:Q1	2023:Q1	
cyclone_dum	Samoa: Cyclone occurrence dummy	1990:Q1	2023:Q1	
total_tax_rev	Samoa: Total tax revenue (in millions WST)	2008:M07	2023:M03	Ministry of Customs and Revenue (MCR)
soi	Southern Oscillation Index (SOI)	1950:M01	2023:M03	National Oceanic and Atmospheric Administration (NOAA) Physical Sciences Laboratory (PSL)
nino_3	SOI Niño 3	1950:M01	2023:M03	NOAA PSL

† PMI - Purchasing Managers' Index
‡ Fugalei market survey - The Fugalei Market Survey is a monthly report undertaken by the Samoa Bureau of Statistics. They survey provides a review of the volume and prices of the main agricultural produce that were available at the Fugalei Market - the main produce market in the country - during the month under review.

Determining which variables to include in our analysis required a series of steps, including regression analyses and model comparisons based on specific criteria. The process of deciding whether to include or exclude variables involved executing regression analyses and comparing the models based on three evaluation criteria: RMSE, AIC, and R-squared.[5] We checked the data for unit roots, seasonal adjustments, and structural dummies, and converted monthly data to quarterly frequencies. Key variables are turned into growth rates (quarter-on-quarter) to ensure variables are stationary for the ordinary least squares (OLS) regression. We used the Augmented Dicky-Fuller (ADF) unit root test on each variable, and found that all variables in growth rate form to be stationary (i.e., the test rejected the hypothesis of a unit root). Since the regressors chosen had a monthly frequency, it was necessary to convert them to a quarterly form to match the quarterly frequency of

[4] Use of El Nino indicators (such as Southern Oscillation Indices) reflects the effect of weather patterns on agricultural production and real GDP (see Cashin et al., 2017)

[5] Xie (2023) and Cashin (2025) discuss the process of variable selection methods for nowcasting models, along with potential issues associated with variable selection.

real GDP. We did this through the aggregation method, summing the "flow" variables and averaging or taking the last observation period of "stock/index" variables.

Choosing the correct indicators and applying econometric techniques appropriately is essential for accurate forecasting. The selected high-frequency indicators should closely follow Samoa's quarterly real GDP. This process led us to select eight variables plus the COVID-19 and seasonality dummy variables (shown in Table 2) that show a strong and positive correlation with real GDP. The chosen indicators for estimating quarterly GDP must not only correlate well with GDP but also maintain this correlation consistently over time. Table 3 presents the correlation matrix showing how GDP and the key high-frequency indicators relate to each other. It is important to note that the final choice of indicators was also influenced by the expertise of CBS sectoral economists.

Table 2. High Frequency Indicators (current model)

Series Name	Description	Start	End	Source
rgdp	Real GDP	2000:Q1	2022:Q3	SBS
remitt	Total remittances (in millions WST)	1993:M01	2023:M03	CBS
for_res_usd	Foreign reserves (in millions USD)	2000:M01	2023:M03	CBS
bank_credit_m	Commercial banks' total credit to private sector and public institutions (in millions WST)	1999:M01	2023:M03	CBS
tour_rec	Tourist receipts (in millions WST)	2002:M08	2023:M03	CBS
mark_svey_val	Fugalei market survey (index)	1993:M01	2023:M03	SBS
imp	Total merchandise imports (in millions WST)	2000:M01	2023:M03	CBS
total_tax_rev	Total tax revenue (in millions WST)	2008:M07	2023:M03	MCR
covid	COVID-19 dummy	2008:Q1	2023:Q1	
@seas	Seasonality dummies	2008:Q1	2023:Q1	
nino_3	Southern Oscillation Index Niño 3	1950:M01	2023:M03	NOAA PSL

Table 3. Correlation Matrix

	rgdp	remitt	for_res_usd	bank_credit_m	tour_rec	mark_svey_val	imp	total_tax_rev	nino_3
rgdp	1.00								
remitt	0.29	1.00							
for_res_usd	0.18	0.88	1.00						
bank_credit_m	0.60	0.77	0.70	1.00					
tour_rec	0.50	-0.10	-0.23	-0.09	1.00				
mark_svey_val	0.73	0.65	0.52	0.74	0.36	1.00			
imp	0.48	0.80	0.64	0.63	0.28	0.65	1.00		
total_tax_rev	0.60	0.85	0.74	0.84	0.21	0.77	0.85	1.00	
nino_3	0.25	-0.14	-0.14	-0.11	0.40	0.02	0.01	0.06	1.00

Source: Authors' calculations.

The evaluation and selection of an appropriate nowcasting method is critical for nowcasting Samoa's real GDP. Three approaches are used in this paper: the Bridge, MIDAS, and U-MIDAS methods. Each of these methods offers a unique framework for integrating high-frequency data to estimate the Samoa's real GDP. Table 4 summarizes the result of the three methods.[6] The Bridge equation method involves linear regression that “bridge” high-frequency variables with their low-frequency counterparts. MIDAS allows for the use of variables with different sampling frequencies in a single regression equation, while U-MIDAS provides a more flexible approach without imposing any predetermined shape on estimated parameters. These methodologies have been carefully considered to determine the most effective approach for nowcasting Samoa’s real GDP, considering the specific characteristics and data availability of the Samoan economy.

Table 4. Summary of Nowcasting Method Results

Dependent variable: dlog(rgdp)			
Variables	**Bridge**	**MIDAS**	**U-MIDAS**
dlog(rgdp(-1))	(-)**		
dlog(remitt)	(-)		
dlog(for_res_usd(-1))	(+)		
dlog(bank_credit_m(-1))	(+)*		
d(tour_rec)	(+)*		
dlog(mark_svey_val)	(+)***		
dlog(imp(-2))	(+)		
dlog(total_tax_rev)	(+)***		
nino_3	(+)		
covid	(-)*		
@seas(1)	(+)		
@seas(2)	(-)***		
@seas(3)	(+)***		
R-squared	0.73	0.80	0.82
Akaike Information Criteria	-3.82	-3.6	-3.43
Durbin-Watson Statistics	2.11	2.07	2.10

Source: Authors' estimates
*indicates 10 percent, **5 percent, ***1 percent, respectively.
Note: For tour_rec variable, we applied first-difference given the presence of 0 values during COVID-19 period.

In the first approach, the Bridge method was used to link high-frequency data with their low-frequency counterparts, a key frequency conversion technique for nowcasting quarterly GDP. This approach transforms high-frequency information, such as monthly data, into a lower frequency, e.g., quarterly, by either aggregating or averaging data points within a quarter. The OLS method was used to estimate the Bridge model, a process well-documented by Baffigi, Golinelli, and Parigi (2004) for creating bridge equations. This method enhances the forecast accuracy of economic indicators by leveraging the timely information in high-frequency data. It operates through a linear regression that connects high-frequency variables to low-frequency ones, selecting specific variables not for causal relations but for their timely updated information. The process includes forecasting monthly indicators for the remaining quarter, typically using univariate time series models,

[6] Given that we are doing nowcasting, we also included variables even with significance level more than 15 percent as long as we have the correct signs.

and then aggregating these to obtain quarterly values. These aggregated values are then used as regressors in the Bridge equation to nowcast the target variable at a lower frequency. This approach can be illustrated algebraically as follows:

$$y_{t_q} = \alpha + \sum_{i=1}^{j} \beta_i(L) x_{it_q} + u_{t_q}$$

where y represents the low frequency (LF) target variable (e.g., quarterly GDP growth), and x_i the high frequency (HF) indicators, $i = 1, \dots, j$ (e.g., monthly industrial production, survey data, etc.), which are aggregated to LF according to their stock/flow nature. Here $t_q = 1, \dots, T$ indicates time in quarters. β_i(L) are polynomials in the lag operator L. β_i(L)= $\beta_{0i} + \beta_{1i}L + \cdots + \beta_{p_i i}L^{p_i}$, one for each HF indicator, where p_i is the number of lags, and u_{t_q} is an i.i.d. error term. In example above, the target frequency t_q is quarterly, but the model can be re-estimated each month. A nowcast $\hat{y}_{T+1}$, e.g., GDP at T+1, is constructed as:

$$\hat{y}_{T+1} = \hat{\alpha} + \sum_{i=1}^{j} \hat{\beta}_i(L) x_{iT+1}$$

where $\hat{\alpha}$ and $\hat{\beta}_{si}$, s= $0, \dots, p$ are OLS estimators. When not all months of x_i in quarter $T+1$ are observable, the missing monthly observations need to be forecast prior to aggregation into x_{iT+1} using AR/ARMA models (with lag length chosen by an information criterion).

The second approach used the MIDAS method, which is a flexible way to analyze data that comes at different frequencies. This method deals with the problem of having too many parameters to calculate, which often happens when working with data that do not all match up in timing. The MIDAS method is helpful when trying to use information that updates more frequently, e.g., daily, to make predictions about something that updates less often, such as quarterly. The MIDAS method handles the challenge of having too many parameters to estimate (“parameter proliferation”) by assumig that the parameters of the variables, after being adjusted through skip/split sampling, follow a certain pattern, such as a polynomial function. This assumption greatly reduces the number of parameters that need to be estimated. However, a downside of this method is that OLS cannot be used because the pattern of the parameters is not linear. Additionally, as discussed in works by Ghysels et al. (2004), there is a risk that the assumed functional form may not accurately represent the underlying data dynamics. The basic MIDAS model for a single explanatory variable, and h_q-step-ahead forecasting, with $h_q = h_m/m$, is:

$$y_{t_q+mh_q} = y_{t_m+h_m} = \beta_0 + \beta_1 b(L_m;\theta) x^{(m)}_{t_m+w} + \epsilon_{t_m+h_m}$$

where $x^{(m)}_{t_m+w}$ is skip-sampled from the HF indicator x_{t_m} and $b(L_m;\theta)$ is a polynomial in the lag operator L for the high frequency variable.

The U-MIDAS model, the third approach utilized in this work, stands out in situations where the frequency difference between the data sets is minimal, such as utilizing monthly data for quarterly forecasts. Like the MIDAS method, U-MIDAS models tailor high-frequency data to match lower frequency goals through innovative "skip" or "split" sampling techniques, diverging from conventional averaging, or summation methods. Unlike the MIDAS approach, the U-MIDAS model seamlessly integrates these high-frequency variables into the forecasting model without predefining the shape of their parameters. This direct integration enables the use of OLS for parameter estimation in the U-MIDAS model. Ghysels and Wright (2009) develop the U-MIDAS model, allowing for more flexible lag structures and variable selection processes without necessitating the pre-specification of lag structures, hence the term "unrestricted." In its simplest form, the U-MIDAS model is a regression of y (e.g., real GDP at a quarterly frequency) on the 3 monthly high-frequency skip-sampled variables $x_{1t_m}^{(m)}$:

$$y_{t_m} = \beta_0 + \beta_1 x_{1t_m}^{(m)} + \beta_2 x_{1t_m-1}^{(m)} + \beta_3 x_{1t_m-2}^{(m)} + \epsilon_{t_m}$$

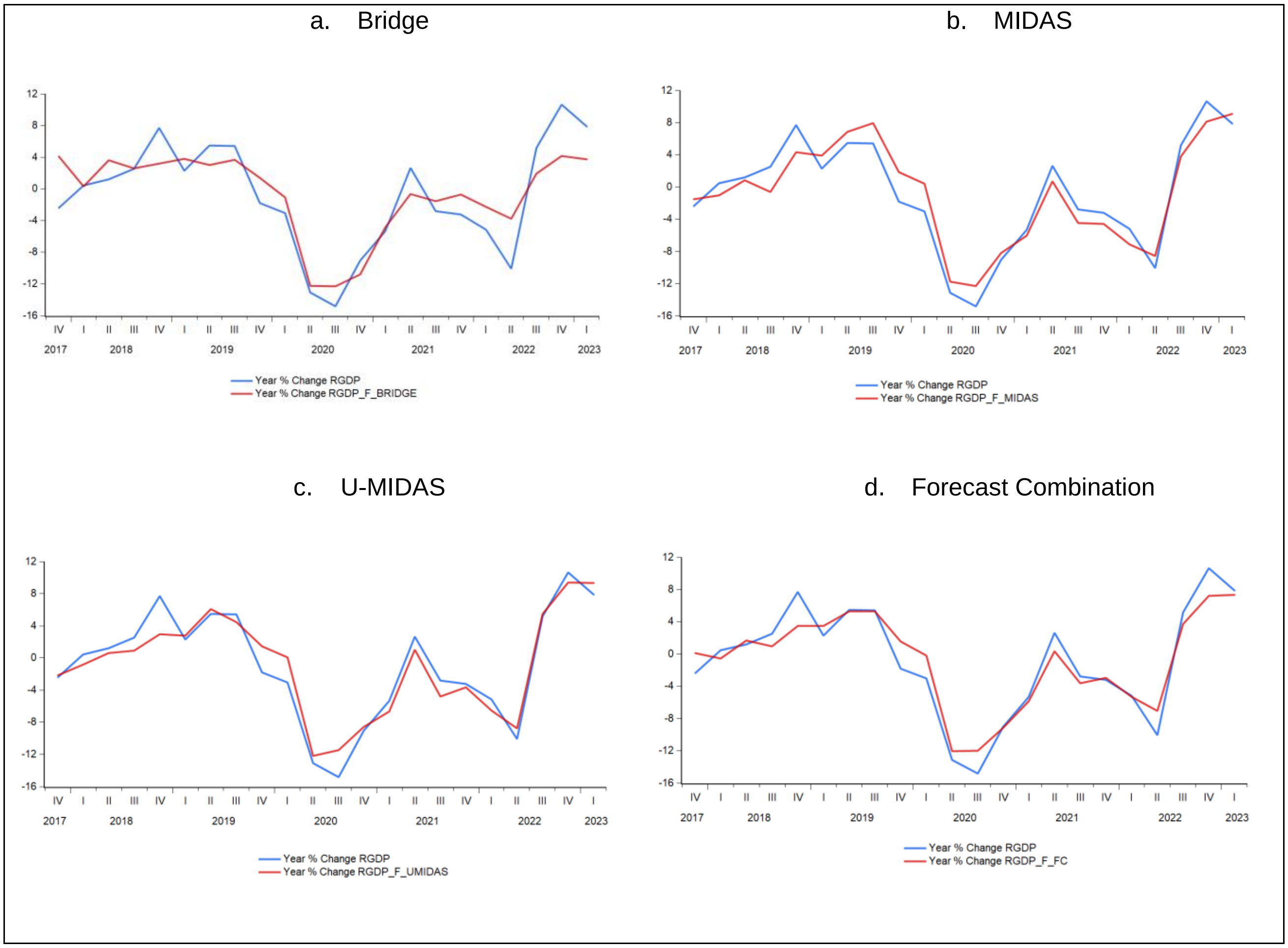
Our results indicate that combining the three forecasting methods delivers the most accurate predictions, particularly during the COVID and post-COVID periods. To verify the effectiveness of our models, we conducted back-testing analyses on three distinct sub-samples: the full sample, pre-COVID sample, and during/post-COVID sample. The analysis generally indicates satisfactory performance across all nowcasts, with the U-MIDAS method standing out in RMSE terms for both the full-sample and during/post-COVID sample (Table 5). Meanwhile, a combined approach of all three methods or forecast combination (FC) proved to enhance the accuracy of the nowcasts especially for the full sample and pre-COVID sample. Notably, our results capture crucial turning points during the pandemic and its aftermath, as shown in Figure 11. It is essential to continuously reassess and refine these models following the introduction of new data. Additionally, our findings reveal that the nowcasts results generated from the three models perform better than a naive forecast, which would have a Theil U2 statistics of one.

Table 5. Forecast Evaluation

Forecast Method	Full Sample (2008Q4-2023Q1)		Pre-COVID Sample (2008Q4-2019Q4)		COVID/Post-COVID Sample (2020Q1-2023Q1)	
	RMSE	Theil U2	RMSE	Theil U2	RMSE	Theil U2
RGDP_F_FC	8.57	0.36	9.03	0.43	5.96	0.19
RGDP_F_BRIDGE	12.46	0.52	12.29	0.57	11.04	0.36
RGDP_F_MIDAS	10.26	0.44	11.04	0.53	6.49	0.21
RGDP_F_UMIDAS	10.02	0.44	11.13	0.54	4.41	0.13

Note: The lower the RMSE and Theil U2 statistics, the better the forecasting performance. Theil U2 statistics also suggests that the forecasting model has a lower sum of squared errors than the naïve forecast, indicating better performance.
Source: Authors’ calculations.

Figure 11. Summary of Model Performance



Nowcast versus actual real GDP growth rate of full sample from 2008Q4-2023Q1. Real GDP growth rate in year-on-year percent change.

IV. Conclusion

This paper introduces a nowcasting tool designed to estimate Samoa's real GDP for the current and following two quarters, an important tool for policymakers to understand the current economic situation. Nowcasting enables the estimation of the present and near-term forecasting, aiding policymakers in assessing the economy's current state. This tool is helpful in providing inputs for macroeconomic frameworks that ensure economic and accounting consistency in macroeconomic surveillance.

This study demonstrates the value of high-frequency data in evaluating current economic activities. Remittances, foreign reserves, bank credit, tourist receipts, agriculture market surveys, imports, total tax revenue, and an El-Niño indicator were used as the variables to develop a GDP nowcasting framework for Samoa. This work highlights how high-frequency datasets can be used in countries with limited and delayed data availability to assess current economic conditions and forecast the economic outlook for the upcoming quarters. Despite the absence of innovative and timely data sources such as nightlight indices and emissions, our findings illustrate that LICs like Samoa can benefit from readily available, relatively high-frequency data for timely macroeconomic assessments. The models developed by CBS will likely require further refinement as new high-frequency indicators and data become available, underscoring the need for continuous evaluation and adjustment of the framework. Forecasting is not merely a mechanical output from a model; it also requires CBS officials to integrate their expert judgment of the Samoan economy's developments. This nowcasting tool, alongside informed judgment, is vital for supporting the production of the "official forecast" of economic growth.

Looking ahead, the effectiveness of the nowcasting exercise could be improved by enhancing data availability and possibly through exploring more advanced analytical methods. Future enhancements could include incorporating new data types such as business sentiment indices, retail sales, timely fiscal expenditure, and revenue data, and adopting more sophisticated, albeit computationally intensive, techniques like principal component analysis and complex multivariate models (e.g., mixed-frequency Vector Autoregression (VAR), Dynamic Factor Models (DFMs)). Additionally, regular updates to the nowcasts are essential for providing policymakers with real-time economic assessments, which are crucial for shaping monetary and financial policies as well as informing fiscal policy decisions during budget planning processes.

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PUBLICATIONS

Nowcasting Real GDP in Samoa
Working Paper No. WP/2025/092