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Abstract

In this document, we introduce a forecasting model for the Gross Domestic Product (GDP) to estimate the economic growth of Madagascar in 2022. Normally, important macroeconomic variables are reported at different frequencies. For instance, GDP and foreign trade figures are typically provided on a quarterly and monthly basis respectively. However, traditional econometric models necessitate data to be harmonized to a common frequency by aggregating at the highest available frequency, which is known as temporal aggregation. Nonetheless, this approach has a disadvantage of losing information. Consequently, we propose the Mixed Data Sampling (MIDAS) method as an alternative.

Keywords: MIDAS, economic growth, Madagascar.

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1 Introduction

The accurate forecasting of economic growth plays a pivotal role in guiding policymakers and stakeholders towards sustainable development. Madagascar, an emerging economy, faces the challenge of effectively predicting its economic trajectory. Traditionally, an accounting approach employing leading indicators has been prevalent in analyzing sectoral evolution on the supply side, thereby capturing potential trends in the real economy. Nonetheless, this conventional method may overlook dynamic relationships and intricate interdependencies that significantly influence economic growth.
In pursuit of a more comprehensive and accurate assessment, this study adopts an alternative perspective known as the demand-side approach. By embracing the innovative Mixed Data Sampling (MIDAS) model, this research endeavors to leverage time series data with different frequencies, thereby unraveling previously hidden connections and enhancing the precision of economic growth forecasts.
The primary objective of this paper is to estimate Madagascar's GDP level and forecast its economic growth for the year 2022 using the MIDAS approach. This research endeavors to meticulously select relevant variables and employ sophisticated statistical techniques to ensure robustness and reliability.

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2 Literature review of the model

TThe Mixed Data Sampling (MIDAS) model, proposed by Ghysels E. and al. (1977), allows for the inclusion of time series with different frequencies in the same regression, overcoming the need for data transformation through aggregation or interpolation. This model can explain the dynamic and structural relationship that is overlooked by temporal data aggregation.

Several authors have used the MIDAS model for macroeconomic forecasting and compared its performance with other models . Michael M. (1911) tested whether a MIDAS approach could improve GDP growth forecasts in the United States. They concluded that using monthly data leads to a significant improvement in current and next-quarter GDP growth forecasts, and that MIDAS outperforms other methods (such as AR and ARDL). Kyosuke C. (2021) conducted a GDP forecasting study in Japan based on MIDAS and compared the results with other approaches. Their study showed that MIDAS had better out-of-sample forecast performance. Foroni C. (2012) compared the forecasting performance of MIDAS and U-MIDAS through Monte Carlo simulations. They demonstrated that U-MIDAS outperformed restricted MIDAS when there were small frequency differences among the selected variables in the regression. However, they were comparable for relatively large frequency differences.

The MIDAS model is described by the following equation:

$$PIB_t = \beta_0 + \beta_2 \sum_{k=1}^{n} b(k;\Theta) L^{\frac{k-1}{m}} X^m_{t-h} + \gamma_1 dm_1 + \gamma_2 dm_2 + \gamma_3 dm_3 + \epsilon_t \tag{1}$$

Where:

- $b(k;\Theta)$ is an Almon exponential lag;
- t indexes the time unit in quarters;
- m is the highest sampling frequency ;
- $L^{\frac{1}{m}}$ is an operator at the highest frequency ;
- h is the forecast horizon ;
- dm_i epresents the dummy variable to capture the seasonal component of the i^{th} trimester;
- X_t represents the vector of explanatory variables.

3 Criteria and Variable Selection

The model used for forecasting/estimation was chosen based on its out-of-sample forecasting performance, measured by the Root Mean Square Error (RMSE). RMSE is a measure of the distance between data points and the regression line. Therefore, we select the model with the lowest RMSE, including the following variables: money supply (m3), electricity consumption in the primary sector (elec1), industry (elec2), services (elec3), and fuel consumption Anjum A. and al. (2001).

In the literature, variables such as exports Michael P. (2008), imports Coe D. T. and Helpman E. (1995), money supply Bednarik R. (2010), electricity consumption Nathan R., 1998, and exchange rates (1998) have been used in GDP regression models.

Advocates of export-led growth, such as Michael M. (1911), Bela B. (1978) argues that countries with a significant share of exports tend to grow faster than others. Export growth acts as a stimulus for technology transfer throughout the economy. In Keynesian theory, export growth leads to production expansion Michael M. (1911).

For Keynesians, changes in money supply lead to changes in real production and prices. Konstantins B. (2008) included money supply in their models for forecasting real GDP in Latvia, Romania, and Germany, respectively. In their forecasting models, they used other variables capturing expenditure (exports, imports, and retail trade) and finance (money supply M3).

The use of electricity powers equipment and associated manufacturing facilities. This analysis suggests that the quantity of electricity consumed can capture the trend of GDP. The GDP regression model adopted by Robert Z. and David E. (1999) includes electricity consumption and other associated variables. These studies found a significant relationship between electricity consumption and GDP. Additionally, electricity consumed in the industrial production process is generated by hydroelectric and thermal power plants. Therefore, the energy variable represented by fuel consumption cannot be omitted. Anjum A. and al. (2001) demonstrated that the relationship between economic growth and energy consumption is well-established in the literature, including in developing countries like Pakistan.

Furthermore, variables such as consumption (proxied by the Consumer Price Index, CPI) and investment (public and private) are components of demand, which is another approach to GDP calculation. Moreover, these variables have a major contribution to determining the real evolution of the economy. Regarding economic openness, exchange rates capture the country's relationship with the rest of the world Prudence A. and al. (1998). The exchange rates used in this case are the Euro, the Dollar, and the Ariary.

The data in this study have different frequencies. Gross Domestic Product (GDP), the explanatory variable, is expressed on a quarterly basis, while the explanatory variables, including money supply (m3), electricity consumption (elec1, elec2, and elec3), public consumption (cg), public investment (ig), Consumer Price Index (ipc), fuel consumption (carb), and exchange rates (EUR (eur), USD (usd), ARIARY (xg)), are measured on a monthly basis. The variables are transformed using logarithms. The stationarity test at the level has shown that none of these variables is stationary. They all exhibit trend-stationary series. Therefore, a decomposition of these series using the Hodrick-Prescott method is necessary.

4 Estimation and Analysis of Model Performance

The quarterly GDP data covers the period from Q1 2007 to Q2 2022, resulting in 64 observations based on the data provided by INSTAT [1]. On the other hand, the explanatory variables span from January 2007 to December 2022, resulting in 192 observations.

During the estimation process, the model specification used is the PDL-ALMON. This specification allows for the estimation of the MIDAS model and captures the relationship between the quarterly GDP and the explanatory variables.

To analyze the performance of our MIDAS model, we conducted a comparison between the observed GDP data and the estimates generated by the model over the entire period from 2007 to 2022. This comparison enables us to assess the accuracy and reliability of the model's predictions and evaluate its ability to capture the dynamics of GDP growth.

5 Result

The result of the model provides us with the following tables:

Quarter GDP	2021	2022
Q1	4 665.8	5 213.9
Q2	5 547.1	5 737.1
Q3	5 535.2	5 405.6
Q4	5 737.3	6 133.0
Annual GDP	21 485.4	22 489.7

Table 1: Estimation result

The selected MIDAS model estimated Madagascar's economic growth rate to be 4.7% for the year 2022. The model exhibits high accuracy in making predictions. The Root Mean Squared Error (RMSE) of 0.014038 suggests that, on average, the model's predictions are off by approximately 0.014038 units from the true values. This indicates that the model's predictions are very close to the actual values, demonstrating its ability to accurately estimate the target variable.

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Similarly, the Mean Absolute Error (MAE) of 0.011039 further supports the model's accuracy. The MAE represents the average absolute difference between the predicted and true values. In this case, the average absolute deviation is approximately 0.011039 units, which is quite small. This reinforces the notion that the model's predictions are generally very close to the true values.
The Mean Absolute Percent Error (MAPE) of 0.130357 (or 13.04%) is also worth noting. This metric represents the average relative error of the model's predictions compared to the actual values, expressed as a percentage. The MAPE of 13.04% indicates that, on average, the model's predictions have a relative error of approximately 13.04% compared to the true values. While this value is relatively low, it's essential to consider the context of the problem and the domain to assess whether this level of relative error is acceptable.
Lastly, the R-squared (R2) value of 0.984338 is very impressive. R-squared measures the proportion of variance in the target variable that the model can explain using the input features. In this case, the model explains about 98.43% of the variance in the data, suggesting that the model's predictions are highly influenced by the input features and are very consistent with the actual data points. This high R-squared value indicates a strong relationship between the input features and the target variable, reinforcing the model's overall effectiveness.

Root Mean Squared Error (RMSE)	0.014038
Mean Absolute Error (MAE)	0.011039
Mean Abs. Percent Error (MAPE)	0.130357
R-squared	0.984338

Table 2: Model performance

In summary, the results indicate that the model performs remarkably well in accurately predicting the target variable. The low RMSE and MAE values imply accurate predictions in absolute terms, and the high R-squared value demonstrates a strong correlation between the input features and the target.

6 Conclusion

In conclusion, the conventional accounting model for Madagascar's national accounts provides a somewhat realistic forecast at the supply level. The indicators chosen in this approach reflect the actual evolution of the sectors' branches in the economy. On the other hand, the Mixed Data Sampling Model promotes a demand-oriented approach based on the variables considered potential in the model's manipulation. This approach offers several advantages in terms of accuracy and comparison with supply-level results. Furthermore, the MIDAS model is among the immediate forecasting models with high-frequency indicators. The model's result indicates a positive growth trend in 2022, which remains preliminary until the final realization figures are published by the responsible entities.

References

Albert K., Cheng Y. Xu, Zhaoyong Z. (2018). " Macroeconomic forecasting with mixed data sampling frequencies : Evidence from a small open economy." Journal of Forecasting, 37(6).

Anjum A. and Mohammad S. Butt (2001). "Relationship between energy consumption and economic growth in Pakistan." Asia-Pacific Development Journal, Vol. 8, No. 2.

Bednarik R. (2010). "Money Supply and real GDP: The case of the Czech Republic". Available at SSRN 1539390.

Bela B. (1978). "Exports and economic growth: Further evidence." Journal of Development Economics Volume 5, Issue 2.

Christian H., Massimiliano M. (2019) . "Forecasting Gross Domestic Product Growth with large Unbalanced Data Sets : The Mixed Frequency Three-pass Regression Filter". Journal of the Royal Statistical Society Series A: Statistics in Society, Volume 182, Issue 1.

Coe D. T. and Helpman, E. (1995). International r&d spillovers.. European economic review, 39(5).

Daniela Z. and Mihail I. C. (2010). Linking money supply with the gross domestic product in Romania. Annales Universitatis Apulensis Series Oeconomica, 12(1).

Duarte C., Rodrigues P. M. M. and Rua A. (2017). A mixed frequency approach to the forecasting of private consumption with ATM/POS data. International Journal of Forecasting, 33(1).

Foroni Claudia (2012). Econometric Models for Mixed-Frequency Data.

Ghysels E., Santa-Clara P. and Valkanov R. (2006). "Predicting volatility: getting the most out of return data sampled at different frequencies". Journal of Econometrics, 131(1-2)

Konstantins Benkovskis (2008), Is there a Bank Lending Channel of Monetary Policy in Latvia? Evidence from Bank Level Dat. Working Papers 2008/01, Latvijas Banka.

Kyosuke Chikamatsu, Naohisa Hirakata, Yosuke Kido and Kazuki Otaka (2021). "Mixed-frequency approaches to nowcasting GDP: An application to Japan". Japan and the World Economy, 57, 1010

Michael Michaely (1977). "Exports and growth: an empirical investigation". Journal of development economics, Volume 4, Issue 1.

Michael P. Clementsa and Ana Beatriz Galvão (2008)." Macroeconomic Forecasting With Mixed-Frequency Data". Journal of Business & Economic Statistics.

Nathan Rosenberg (1998). "The Role of Electricity in Industrial Development". IAEE's Energy Economics Education Foundation, Volume19, Number 2 of the bi-monthly journal.

Prudence Attah-Obeng, Patrick Enu F. ,Osei-Gyimah, C.D.K. Opoku (2013) . "An Econometric Analysis of the Relationship between Gdp Growth Rate and Exchange Rate in Ghana". Journal of Economics and Sustainable Development, Vol.4, No.9, 2013 .

Robert Z. Lawrence and David E. Weinstein (1999). "Trade and Growth: Import-Led or Export-Led? Evidence From Japan and Korea". National Bureau of Economic Research 1050 Massachusetts Avenue Cambridge, MA 02138.

T. N. Srinivasan and N. Bagwati (1978). "Trade policy and development".