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NOWCASTING GROWTH AT RISK IN INDONESIA: APPLICATION OF MIDAS-QUANTILE REGRESSION MODEL

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ABSTRACT

One of the main problems faced by policymakers in economic monitoring is the limited availability of predictive tools that can comprehensively and in real time measure economic growth risks, particularly amid financial market volatility and rapid changes in economic indicators. This study aims to nowcast Indonesian economic growth using the Growth at Risk (GaR) approach by applying the Mixed Data Sampling-Quantile Regression (MIDAS-QR) model. This approach predicts economic risks across different quantiles, capturing best- and worst-case scenarios by integrating multi-frequency indicators, namely the Financial Conditions Index (FCI), External Financial Environment Index (EFEI), and Macroeconomic Prosperity Leading Index (MPLI), summarized using Principal Component Analysis (PCA). Prediction accuracy is evaluated using Quantile Mean Absolute Error (QMAE), Quantile Root Mean Squared Error (QRMSE), and Clark-West (CW) test metrics. The analysis utilizes a dataset of Indonesia covering the period from January 2001 to March 2025, combining quarterly GDP growth data as the dependent variable and monthly predictor variables sourced from the Central Statistics Agency (BPS), Bank Indonesia, and the Indonesia Stock Exchange. The findings show that the MIDAS-QR model significantly improves the accuracy of GaR forecasting in Indonesia relative to conventional approaches. It effectively captures risk asymmetries across quantiles, minimizes predictive errors, and facilitates the timely detection of economic downturns, offering valuable insights for early action. This study highlights the strategic role of high-frequency data in enhancing forecast precision and real-time economic risk monitoring in Indonesia. The application of the MIDAS-QR model presents a valuable tool for policymakers in formulating proactive responses to global economic uncertainty and fostering resilient economic growth.

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1. INTRODUCTION

In recent years, Indonesia has experienced significant economic growth, supported by strong domestic consumption, increasing fixed investment, and export recovery. Indonesia's GDP growth projection in 2025 is estimated to reach around 5.1% to 5.2%, reaffirming the country's important role in driving regional economic growth. [1], [2]. However, this growth is accompanied by major challenges in the form of economic uncertainty, both from global and domestic factors, where GDP growth projections often depend on unstable economic and financial dynamics. Global pressures such as the Fed's tight monetary policy, China's economic slowdown, and geopolitical tensions have also increased the risks to the national economy [3]. Therefore, responsive policymaking requires the availability of accurate and real-time information on current economic conditions [4].

The main problem faced is the limited availability of predictive tools that can comprehensively and in real time measure economic growth risks, especially in the context of financial market volatility and rapid changes in economic indicators. Traditional GaR approaches use low-frequency data, such as quarterly financial condition indices, to predict quarterly GDP growth. However, financial indicators are often available at higher frequencies, while economic data are often aggregated to low frequencies. The use of simple averaging methods in this aggregation process can lead to the loss of important information. Besides that, it can also result in biased estimates [5]. In Indonesia, this condition becomes even more crucial given the reliance on daily and monthly indicators in responding to rapid changes in the financial and trade sectors [6].

To address this challenge, the Growth at Risk (GaR) approach is introduced as a predictive tool to estimate risks to economic growth by providing a full picture of the distribution of GDP growth projections as a whole [7]. Based on these issues, this study aims to develop the GaR approach using the Mixed-Data Sampling-Quantile Regression (MIDAS-QR) model, leveraging multi-frequency data from the Financial Conditions Index (FCI), External Financial Environment Index (EFEI), and Macroeconomic Prosperity Leading Index (MPLI) through Principal Component Analysis (PCA). This model is expected to predict Indonesia's economic growth risks across various quantiles, including both best- and worst-case scenarios, and enable more accurate and responsive nowcasting of GDP growth. Additionally, this study seeks to integrate computational intelligence technology into GaR analysis to support faster and more effective decision-making in facing economic challenges and to drive digital transformation towards sustainable development [8].

Growth at Risk (GaR) is an extension of Value-at-Risk (VaR), a widely used measure of potential financial losses over a given period. As such, VaR has become an important tool in financial risk assessment. However, VaR focuses solely on individual risk and does not account for the interconnectedness between financial institutions. To address this limitation, Conditional Value-at-Risk (CoVaR) was developed to capture the impact of systemic risk on the financial system. Building on this, GaR adopts a broader perspective by evaluating how financial risk influences economic growth through both micro-prudential and macro-prudential approaches. Indeed, research indicates that vulnerabilities in economic growth are often triggered by amplification mechanisms within the financial sector. Therefore, monitoring financial conditions is essential to understanding how financial risk contributes to economic growth [7], [9].

GaR has advantages in macroeconomic monitoring by providing a full distribution of future GDP growth projections. This approach captures both positive and negative risks, beyond point-estimation-based approaches. GaR also allows analysis of the interrelationships between macroeconomic and financial factors. It does this by exploring the main drivers of GDP growth and their variations based on time horizon and quantile [10]. With these capabilities, GaR has been used by international institutions such as the IMF to support economic policies. To estimate GaR, this study uses Quantile Regression (QR). The QR is robust to outliers and enables the analysis of heterogeneous effects across the distribution of economic growth [10]. Although the QR is often described as capturing nonlinear phenomena, it is important to clarify that the QR model applied in this study is linear at each quantile. The nonlinearity arises from allowing the estimated coefficients to vary across different quantiles. This variation reveals how the impact of financial indicators can differ under various economic conditions. This approach captures variations in the relationship between predictors and GDP growth at different points in the distribution so that it provides a more comprehensive understanding of risk.

This study develops a GaR approach with mixed-frequency data, utilizing monthly financial indicators to predict quarterly GDP growth using MIDAS-QR. This mixed-frequency GaR approach is applied to analyze the risk of economic growth in Indonesia. In particular, it uses three monthly indicators: FCI, EFEI, and MPLI, as well as quarterly GDP data calculated from annual data. Overall, this approach provides a comprehensive framework for assessing Indonesia's economic growth risks by integrating high-frequency financial indicators with advanced predictive modeling techniques.

To elaborate on the choice of indicators, the selection of indicators above is strongly supported by theoretical and empirical evidence on their relevance to economic growth. FCI aggregates key domestic financial variables such as interest rates, the middle exchange rate to USD, and the Composite Stock Price Index. Specifically, these variables directly influence investment and consumption. Tighter financial conditions are generally associated with lower economic activity. Conversely, looser conditions stimulate growth [6]. EFEI captures global financial shocks and external risks, including international interest rates, commodity prices, and global risk sentiment. EFEI is particularly important for open economies like Indonesia, where external shocks can significantly affect capital flows, exchange rates, and export performance [11]. MPLI synthesizes forward-looking macroeconomic indicators such as industrial production, business expectations, and consumer confidence, providing early signals of turning points in economic activity [11]**.** By integrating FCI, EFEI, and MPLI, the model comprehensively captures both domestic and external financial conditions as well as leading macroeconomic signals. Therefore, this integration enhances the predictive power and responsiveness of GaR estimates for Indonesia.

The integration of MIDAS-QR for predicting GaR enables the modeling of non-linear relationships between high-frequency indicators (e.g., monthly financial data) and low-frequency GDP growth. This capability results in GaR estimates that are both more accurate and responsive to dynamic economic changes. Furthermore, the sensitivity of key variables of the model, such as the benchmark interest rate, inflation, and exchange rate expectations, to external conditions underscores the importance of nowcasting monthly GDP growth. Such nowcasting is critical for supporting timely and more measured policy responses to dynamic economic changes.

To assess the model's performance, this study evaluates the mixed-frequency GaR framework using two primary metrics: Quantile Mean Absolute Error (QMAE) and Quantile Root Mean Square Error (QRMSE) [11]. The results show that the proposed model outperforms traditional low-frequency approaches in prediction accuracy. Notably, it exhibits greater robustness to economic volatility, particularly in the low and high quantiles of the growth distribution, which are frequently neglected by conventional models.

This study distinguishes itself from previous research in several important ways. A key contribution is the introduction of nowcasting projections for monthly GDP growth in Indonesia, contrasting with studies such as Xu et al. [11], which focused on quarterly projections in China. Additionally, this study expands the analytical scope by incorporating three relevant local indicators, namely the Financial Conditions Index (FCI), External Financial Environment Index (EFEI), and Macroeconomic Prosperity Leading Index (MPLI), to offer a more comprehensive understanding of Indonesia's domestic economic dynamics. Unlike earlier studies that considered only one or two sources of risk to economic growth [12], [13], [6], this study integrates multiple risk factors from both the financial sector and the real economy. Moreover, this study represents the first application of the mixed-frequency GaR approach in Indonesia, utilizing monthly indicators through the MIDAS-QR method. This methodology has been demonstrated to enhance the timeliness and accuracy of macroeconomic forecasts compared to traditional approaches relying solely on quarterly data, as evidenced by prior works. Studies such as [11], [14], [15], and [16] further confirm that MIDAS-QR leverages the latest high-frequency data to update real-time forecasts derived from low-frequency data, resulting in more precise and responsive analyses amid evolving economic conditions. By employing a digital technology-based approach, this study aims to advance the measurement and prediction of GaR in Indonesia. The primary contribution of this study lies in the application of the GaR approach using multi-frequency data and the MIDAS-QR method, which has not previously been implemented in the Indonesian context. In addition, this study broadens the analytical scope by incorporating three key locally relevant indicators, offering a more comprehensive and adaptive framework for predicting economic risks. As a result, the findings are expected to facilitate faster economic monitoring and provide policymakers with more effective tools to design sustainable development strategies amid global and domestic uncertainties.

Based on differences from previous research, the research gap identified can be summarized as follows. Previous studies primarily focused on quarterly GDP projections and limited sets of risk indicators, often one or two, without fully capturing the complexity of local economic dynamics. There has been no prior application of the mixed-frequency GaR approach using the MIDAS-QR method in Indonesia. Existing research lacks integration of multiple relevant local indicators, such as FCI, EFEI, and MPLI, to comprehensively assess Indonesia's economic risks. The timeliness and accuracy improvements offered by combining high-frequency monthly data with MIDAS-QR have not been explored in the Indonesian context. There is a need for a more adaptive and comprehensive framework that leverages digital technology and mixed-frequency data to enhance economic risk measurement and nowcasting for Indonesia. This study addresses these gaps by introducing a novel, multi-indicator, mixed-frequency GaR framework tailored to Indonesia's economic environment, aiming to improve real-time economic monitoring and policy responsiveness.

The remainder of this paper is organized as follows. Section 2 provides a comprehensive literature review, covering topics such as nowcasting GDP growth, the MIDAS method, Quantile Regression (QR), and Growth at Risk (GaR). Section 3 details the research method, including descriptions of the data, the MIDAS-Quantile Regression model, and evaluation techniques employed in this study. Section 4 presents the empirical results and discussion, encompassing descriptive statistics of the variables, parameter estimates for both the QR and MIDAS-QR models across different quantiles, and assessments of prediction accuracy using QMAE, QRMSE, and the CW Test. This section also discusses the nowcasting of quarterly and monthly GDP Growth at Risk. Finally, Section 5 concludes the paper.

2. RESEARCH METHODS

This study uses a non-experimental quantitative approach with a library research method, which utilizes literature and secondary data from official institutions. The main objective of this study is to analyze the distribution of Indonesia's economic growth risk (Growth-at-Risk) using the Mixed Data Sampling - Quantile Regression (MIDAS-QR) model based on mixed frequency data. This approach was chosen because it allows the integration of data with different frequencies without the need for high-to-low data aggregation, which can cause loss of important information.

2.1 Nowcasting GDP Growth

Nowcasting, or current forecasting, is a technique for estimating the value of economic variables, such as Gross Domestic Product (GDP) growth, before official data is released. Saputra et al. [6] emphasize that real-time economic policymaking requires an accurate assessment of current economic conditions. In this context, nowcasting is important to provide up-to-date information that allows for more timely policy responses. GDP data is often available at a low frequency (quarterly), while financial data and other economic indicators have a higher frequency (monthly, weekly, daily). Therefore, nowcasting by utilizing high-frequency data is crucial to obtain a faster and more accurate picture of the economy.

2.2 MIDAS Method

The Mixed Data Sampling (MIDAS) method was first introduced by Ghysels et al. [5] to address a fundamental challenge in econometric modeling: how to effectively utilize data observed at different frequencies [17], [18]. Prior to MIDAS, the conventional econometric models, such as Vector Autoregressions (VAR) or linear regressions, required data to be at the same frequency, often forcing researchers to aggregate high-frequency data, like monthly inflation or industrial production, into lower-frequency intervals such as quarterly GDP. This aggregation process inevitably led to the loss of valuable information and reduced the accuracy and timeliness of economic forecasts. MIDAS overcame these limitations by allowing direct modeling with mixed-frequency data, thereby maximizing the use of available information without the need for aggregation. MIDAS enables the direct incorporation of high-frequency predictors into models for low-frequency target variables without requiring data aggregation or interpolation, which improves forecasting accuracy and nowcasting capabilities. Over time, this method has gained significant popularity in macroeconomic and financial applications due to its ability to capture economic dynamics more responsively and in near real-time. The flexibility of MIDAS to handle data sampled at different frequencies has made it a powerful tool in the analysis of economic indicators and financial market variables, supporting more timely and informed decision-making.

To further illustrate how MIDAS operates in practice, the following explanation presents the notation and general mathematical form of the MIDAS model. Let $\{y_t, t \in T\}$ be a low-frequency response variable and $\left\{x_k^{(t)}, k \in K\right\}$ be a high-frequency predictor variable with T and K is time series set. The MIDAS model involves a linear projection using a stochastic process $\left\{x_k^{(t)}, k \in K\right\}$, obtained from higher frequencies. For each low frequency with period t, the process $x_k^{(t)}$ is observed at high frequencies with period k, $k = (t-1)m+1, \dots, tm$. In general, the MIDAS model is expressed in the following equation with lag autoregressive L and coefficient parameter α_j.

$$y_t = \sum_{j=1}^{L} \alpha_j y_{t-j} + \sum_{i=1}^{p} \sum_{k=0}^{m-1} \beta_{i,k}^{(t)} x_{i,m-k}^{(t)} + \epsilon_t \ , \tag{1}$$

with $x_{i,k}^{(t)}$ indicating the i-th predictor variable, m indicates the number of high-frequency samples in one low-frequency sample; in this case, the value is 3. While ϵ_t is the random error [5].

In the MIDAS model of (1), if the parameters of the polynomial lag are unrestricted, then each regression coefficient parameter $\beta_{i,k}^{(t)}$of $x_{i,m-k}^{(t)}$ will be estimated. This model is called the unrestricted MIDAS model. To limit the number of parameters that need to be estimated, a weighting function is used in the restricted MIDAS model. Ghysels et al. [5] suggest a weighting function in the form of an Exponential Almon lag polynomial with the following formula:

$$w_k(\boldsymbol{\delta}, d) = \frac{\psi(\boldsymbol{\delta}, d)}{\sum_{d=1}^{m} \psi(\boldsymbol{\delta}, d)}, \tag{2}$$

with $\psi(\boldsymbol{\delta}, d) = \exp\left(\sum_{l=1}^{q} \delta_l d^l\right)$, d is the lag index indicating the position of the high-frequency data used in the weighting and aggregation in the MIDAS model, l is the index of the polynomial term in the weight function, q indicates the total number of parameters used in the weight function, and $\boldsymbol{\delta} = \left(\delta_1, \dots, \delta_q\right)'$ by performing tuning to determine each δ_q [6]. Thus, the MIDAS restricted model with Exponential Almon lag polynomial weighting function is expressed in the following equation.

$$y_t = \sum_{j=1}^{L} \alpha_j y_{t-j} + \sum_{i=1}^{p} \sum_{k=0}^{m-1} \beta_{i,k}^{(t)} w_k(\boldsymbol{\delta}, d) x_{i,m-k}^{(t)} + \epsilon_t \tag{3}$$

2.3 Quantile Regression (QR)

Quantile Regression (QR) was first introduced by Koenker [19]. This method is a generalization of traditional linear regression that focuses its analysis on variables not only on the average (mean), but also on various quantiles of the response variable distribution. In traditional linear regression, parameter estimation is carried out using the Ordinary Least Square (OLS) method, which only focuses on the mean and has several weaknesses, such as sensitivity to outliers and the assumption of a normal distribution of errors. On the other hand, QR is able to provide a more robust and flexible solution, especially for data with non-normal error distributions or long tails [19]. Mathematically, QR focuses on the θ-quantile of the response variable distribution. Suppose y is a response variable with a cumulative distribution F_y. For a probability θ between 0 and 1, the θ-quantile of F_y is defined as follows.

$$Q_y(\theta) = inf\{y: F(y) \geq \theta\}, \tag{4}$$

with $F(y) = P(Y \leq y)$ is the cumulative distribution of the response variable Y. When the response variable y is influenced by the covariate X, the θ-th conditional quantile is formulated as follows.

$$\hat{Q}(\theta|\boldsymbol{X}) = \boldsymbol{X}\widehat{\boldsymbol{\beta}}(\theta), \tag{5}$$

with $\beta(\theta)$as the θ-th quantile regression parameter. The general quantile regression equation can be written as:

$$\boldsymbol{y}(\theta) = \boldsymbol{X}\widehat{\boldsymbol{\beta}}(\theta) + \boldsymbol{\epsilon} \, , \tag{6}$$

with ϵ being the model residual.

Based on the equation, the vector $\boldsymbol{\beta}(\theta)$ can be estimated by $\widehat{\boldsymbol{\beta}}(\theta)$ which is then called the model parameter estimate at the θ-th quantile. The parameter estimation of $\widehat{\boldsymbol{\beta}}(\theta)$ is done by minimizing the weighted loss function using the following equation:

$$\widehat{\boldsymbol{\beta}}(\theta) = \underset{\beta}{\operatorname{argmin}} \sum_{t=1}^{T} \rho_\theta \left(y_t - \boldsymbol{Z}_{t-h} \widehat{\boldsymbol{\beta}}(\theta) \right), \tag{7}$$

with a weighted loss function $\rho_\theta(\epsilon_t) = \begin{cases} \theta\epsilon_t, & \text{if } \epsilon_t \geq 0 \\ (\theta - 1)\epsilon_t, & \text{if } \epsilon_t < 0 \end{cases}$, where $\boldsymbol{Z}_{t-h} = \left(\boldsymbol{y}_{t-h}, \boldsymbol{X}_m^{(t-h)}\right)_{T\times(L+p)}$ with h being the forecast horizon and ϵ_t being the residual from the parameter estimation results. In the end, (7) will become:

$$\widehat{\boldsymbol{\beta}}(\theta) = \min_{\boldsymbol{\beta}} \left[\frac{1}{T} \sum_{t=1}^{T} \rho_\theta \big(y_t - \hat{y}_t(\theta) \big) \right]. \tag{8}$$

This loss function ensures that the θ-quantile parameter estimates are more accurate by giving different weights to positive and negative residuals.

2.4 Growth at Risk (GaR)

Growth at Risk (GaR) is an approach to evaluate financial risk against economic conditions based on GDP growth using tail-risk values [7]. This method is similar to the Value at Risk (VaR) approach in finance [7], [20]. The GaR approach is built on the quantile regression method [6], [7]. In the context of GaR, quantile regression is used to estimate the conditional distribution of GDP growth under various financial conditions. The GaR approach provides a clearer perspective on the potential risk of a decline in GDP below a certain quantile, making it relevant in macroeconomic stability analysis [21].

To formulate this approach mathematically, suppose the lag of GDP Growth y_{t-h} is used as the response variable, while the financial condition indicator $x_{t-h}^{(m)}$ is used as the predictor variable. Here, h is the forecast horizon that relates past financial conditions to GDP Growth at time h. It is assumed that x has the same data frequency as y. Referring to Eqs. (5) and (7), Koenker [19] proved that the predicted value $\hat{Q}(\theta|\boldsymbol{Z}) = \boldsymbol{Z}_{t-h}\widehat{\boldsymbol{\beta}}(\theta)$ is a consistent linear estimator of the conditional quantile function of y_t. Based on the quantile regression approach, the conditional prediction of the θ-th quantile for $y_{T|T-h}$ which depends on the available sample information up to $T - h$ can be formulated as follows.

$$\hat{Q}_{y_{T|T-h}}(\theta|\boldsymbol{Z}) = \boldsymbol{Z}_{t-h}\widehat{\boldsymbol{\beta}}(\theta), \tag{9}$$

with $\boldsymbol{Z}_{t-h} = \left[\boldsymbol{y}_{t-h}, \mathbf{x}_{t-h}^{(m)}\right]$ is a covariate vector containing historical information on GDP growth and financial indicators at the horizon $t - h$ [19]. The quantile conditional regression parameters $\widehat{\boldsymbol{\beta}}(\theta)$, are estimated using a quantile regression method consistent with the conditional distribution.

Furthermore, based on the conditional quantile distribution function, GaR at the probability level $(1 - \theta)\%$, namely $GaR(100\theta\%)$ can be formulated as follows.

$$GaR(100\theta\%) = Q_{y_{T|T-h}}(\theta|\boldsymbol{Z}) = F^{-1}(\theta|\boldsymbol{Z}), \tag{10}$$

where $F^{-1}(\theta|\boldsymbol{Z})$ is the inverse function of the conditional quantile distribution that predicts the lowest expected value of future GDP Growth at a given probability level. In other words, this value reflects the projection of GDP Growth with a probability of $100\theta\%$ based on the conditional quantile function of $y_{T|T-h}$ [21].

2.5 Research Data

This study utilizes data from Indonesia covering the observation period from January 2001 to March 2025. The dataset comprises 97 quarterly low-frequency data observations for the response variables and 291 monthly high-frequency data observations for the predictor variables. All data were obtained from the Central Statistics Agency (BPS), Bank Indonesia, and the Indonesia Stock Exchange.

The response variable in this study is quarterly Gross Domestic Product (GDP) growth, used as a proxy to measure economic conditions and how well a country is growing. Meanwhile, the predictor variables in this study are the Financial Conditions Index (FCI), External Financial Environment Index (EFEI), and Macroeconomic Prosperity Leading Index (MPLI). Each index is formed using Principal Component Analysis (PCA), which aims to reduce the dimension of the data without losing important information. Thus, it produces the main components that represent a collection of related indicators. FCI is an indicator used to assess a country's domestic financial condition by combining various components that include exchange rate stability, monetary policy, and capital market dynamics [22]. The main components of FCI are the Middle Exchange Rate against USD (JISDOR Reference Rate), Reference Interest Rate (BI-Rate), and Composite Stock Price Index (IHSG). On the other hand, EFEI is an indicator that reflects external factors that affect the domestic economy, with a focus on international trade and foreign exchange flows. The main components of EFEI are Exports (FOB Value in USD), Imports (CIF Value in USD), and the Number of Foreign Tourist Visits (Wisman). Lastly, MPLI is a comprehensive indicator used to assess the prospects for a country's macroeconomic progress and the welfare of society. The main components of MPLI are the Consumer Price Index (CPI), Wholesale Price Index (WPI), Narrow Money Supply (M1), and Broad Money Supply (M2).

2.6 MIDAS-Quantile Regression Model

Despite its advantages, the classical MIDAS framework primarily focuses on estimating the conditional mean or median of the target variable, which limits its ability to capture extreme risks or the full distribution of economic variables such as GDP growth. Understanding these tail risks is crucial for monetary and fiscal policymakers, especially when anticipating economic shocks or crises [7]. To address this limitation, the MIDAS framework has been extended to incorporate Quantile Regression techniques, resulting in the MIDAS-Quantile Regression (MIDAS-QR) model. MIDAS-QR allows for modeling various parts of the conditional distribution, including both downside and upside risks, enabling a more comprehensive risk assessment and supporting more adaptive and risk-sensitive policy decisions [11]. To effectively implement this approach, it is important to address several technical challenges inherent in Quantile Regression modeling, especially when dealing with mixed-frequency data [21], as discussed below.

One of the main challenges in Quantile Regression (QR) modeling, especially in time series data, is the frequency difference between the response and predictor variables. Data with higher frequencies are often considered more informative for predicting response variables with lower frequencies. However, the obstacle that arises is how to properly aggregate high-frequency data so that the information obtained remains optimal. Therefore, [21] offers a solution to this problem by combining a method called Mixed Data Sampling-Quantile Regression (MIDAS-QR). The MIDAS-QR model allows for the utilization of information from data with different frequencies without losing important information that might occur if simple aggregation is performed [5]. The general form of this model is then stated as follows:

$$y_t(\theta) = \sum_{j=1}^{L} \alpha_j(\theta) y_{t-j} + \sum_{i=1}^{p} \beta_i^{(t)}(\theta) \sum_{k=0}^{m-1} w(\boldsymbol{\delta}(\theta), d) x_{i,m-k}^{(t)} + \epsilon_t \ , \tag{11}$$

where $w(\boldsymbol{\delta}(\theta), d)$ is a weighting function whose sum is close to 1. This weighting function depends on the polynomial parameter vector $\boldsymbol{\delta}(\boldsymbol{\theta})$ and the lag index d. The variables $x_m^{(t)}$ and y_t represent high-frequency (monthly) and low-frequency (quarterly) data, respectively. This weighting function is often expressed in the form of the Almon lag polynomial. With this approach, the MIDAS-QR Model can be reformulated as:

$$y_t(\theta) = \sum_{j=1}^{L} \alpha_j(\theta) y_{t-j} + \sum_{i=1}^{p} \beta_i^{(t)}(\theta) \sum_{k=0}^{m-1} w_k(\boldsymbol{\delta}, d) x_{i,m-k}^{(t)} + \epsilon_t \ . \tag{12}$$

With $w_k(\boldsymbol{\delta}, d)$ is the Almon lag weighting. One of the variations of the Almon lag that is often used is the Exponential Almon Lag Polynomial. The main advantage of the Almon lag polynomial is that the linear equation refers to the principle of simplicity (parsimonious model) because the weighting function only depends on m parameters, so it can efficiently capture the relationship between high and low frequency variables without excessive complexity. The Exponential Almon Lag polynomial weighting in this study uses two delta parameters as suggested by [5], which are defined as follows:

$$w_k(\delta_1, \delta_2; d) = \frac{exp(\delta_1 d^1 + \delta_2 d^2)}{\sum_{d=1}^{m} exp(\delta_1 d^1 + \delta_2 d^2)}. \tag{13}$$

Parameters δ_1 and δ_2 determine the shape of the weight distribution, d is the lag index, indicating the position of the high-frequency data used in the weighting function. Using MIDAS-QR, this study aims to measure the impact of high-frequency financial variables on the distribution of GDP growth in Indonesia.

In this study, the parameter tuning was carried out to determine the estimation of two delta parameters (δ) used with a range of -0.5 to 0.5 (multiples of 0.1) and excluding zero, resulting in 100 modeling combinations (10×10). With the combination of the two delta parameters formed is $\delta = ((-0.5;\ -0.5), (-0.5;\ -0.4), \dots, (-0.5;\ 0.5), (-0.4;\ -0.5), \dots, (0.5;\ 0.5))$. This range is an extension of the study by Saputra et al. [6], which recommends a δ value in the interval -0.2 to 0.2 with a multiple of 0.1 (excluding zero), which aims to capture the dynamic relationship between high and low frequency data without causing overfitting. The value of zero is deliberately avoided because it can eliminate important temporal structures in monthly data. Quantile $\theta = \{0.05;\ 0.25;\ 0.50;\ 0.75;\ 0.95\}$ were selected because they comprehensively represent the lower, middle, and upper tails of the economic growth distribution, in accordance with standard practice in the Growth at Risk literature [7]. Thus, the total number of modeling combinations tested reached $5 \times 100 = 500$ models. The selection of the best parameter combination was carried out based on the smallest QMAE and QRMSE criteria of the MIDAS-QR model, which have been proven effective in assessing the accuracy of quantile predictions [11]. After the quarterly response frequencies were adjusted to the monthly predictors through MIDAS, other parameter estimations were carried out using the Quantile Regression (QR) approach based on Eq. (8).

The model specifications built for this study use three monthly indicators, namely, FCI, EFEI, and MPLI, to predict quarterly GDP growth and measure mixed-frequency GaR. Specifically, this model refers to the research of Xu et al. [11], which has been adapted for the Indonesian context. In this mixed-frequency setting, the frequency ratio is 3:1, meaning that each quarterly GDP growth observation is associated with three monthly observations. For each quarter, the MIDAS model incorporates monthly data from the three months preceding the quarter as predictor variables. This effectively results in a lag length of three-monthly observations per quarter. The weighting of these monthly lags is determined using an exponential Almon lag polynomial with two parameters, as suggested by Ghysels et al. [5], ensuring that all available high-frequency information is captured within the relevant quarterly period without loss of detail through simple aggregation. Therefore, this study adopts the MIDAS-QR method as proposed by Xu et al. [11] with these model specifications.

$$GDP\ Growth_t(\theta) = \beta_0(\theta) + \beta_{1,i}(\theta) \sum_{k=0}^{m-1} w_k(\boldsymbol{\delta}(\theta), d) FCI_{i,m-k}^{(t)} + \beta_{2,i}(\theta) \sum_{k=0}^{m-1} w_k(\boldsymbol{\delta}(\theta), d) EFEI_{i,m-k}^{(t)} \quad (14)$$

$$+\beta_{3,i}(\theta) \sum_{k=0}^{m-1} w_k(\boldsymbol{\delta}(\theta), d) MPLI_{i,m-k}^{(t)} + \alpha_j(\theta) GDP\ Growth_{t-j} + \epsilon_t\ ,$$

that i is the principal component (PC) order used for each variable.

2.7 Model Evaluation

In the performance evaluation of Growth at Risk (GaR) with mixed frequencies, this model is compared with traditional GaR through out-of-sample forecast tests. Referring to Xu et al. [11], two main error metrics are used, namely Quantile Mean Absolute Error (QMAE) and Quantile Root Mean Square Error (QRMSE), which are respectively defined as follows.

$$QMAE(\theta) = \frac{1}{T} \sum_{t=1}^{T} \left| \rho_\theta\left(y_t - \hat{y}_t(\theta)\right) \right|, \quad (15)$$

$$QRMSE(\theta) = \sqrt{\frac{1}{T} \sum_{t=1}^{T} \left(\rho_\theta\left(y_t - \hat{y}_t(\theta)\right) \right)^2}, \quad (16)$$

where $\hat{y}_t(\theta)$ is the forecast value at quantile θ and ρ_θ is the quantile loss function. In general, the smaller the QMAE and QRMSE values, indicate better the model performance [11].

To compare the performance of the model with the classical statistical approach, the CW-test [23] is used with the method referred to by Ghysels et al. [24]. This test measures whether the difference between two quantile regression models is statistically significant. First, the forecast error at h steps in the future is defined, which is given as follows.

$$\hat{e}_{t|t-h}^{(m)} = GDP\ Growth_t - \hat{f}_{t|t-h}^{(m)}, \tag{17}$$

with $\hat{f}_{t|t-h}^{(m)} = \hat{Q}_{GDP}(\theta|Z_{t-h})$ which is the conditional quantile forecast of model m, where $m \in \{MIDAS - QR, QR\}$. Next, the check function $\rho(\cdot)$ is evaluated on the forecast error $\hat{e}_{t|t-h}^{(m)}$ with the following formula.

$$\rho(\hat{e}_{t|t-h}^{(m)}) = \left(\theta - I\left(\hat{e}_{t|t-h}^{(m)} < 0\right)\right)\hat{e}_{t|t-h}^{(m)}. \tag{18}$$

The series of differences in the check-loss function at each time point is calculated using the following formula.

$$\widehat{cw}_t = \rho(\hat{e}_{t|t-h}^{(QR)})(\hat{e}_{t|t-h}^{(QR)} - \hat{e}_{t|t-h}^{(MIDAS-QR)}), \tag{19}$$

and the Clark-West (CW) statistic is formulated as follows.

$$CW = \frac{\overline{cw}}{\sqrt{Var(cw)}}, \tag{20}$$

with $\overline{cw} = \frac{1}{T_{out}}\sum_{t=T_{in}+1}^{T} \overline{cw}_{t+h}$, $Var\,(cw)$ is the sample variance adjusted by the Newey-West HAC procedure. Here, T_{out} is the out-of-sample sample size, and $T = T_{in} + T_{out}$.

This CW statistic is used to test the significance of the performance of the mixed-frequency GaR model compared to the traditional GaR model. The null hypothesis (H_0) states that the performance of the two models is equivalent, while the alternative hypothesis (H_1) states that the mixed-frequency GaR model has better performance. Furthermore, the hypothesis of the CW statistic test is as follows.

$$H_0: E[\rho(\hat{e}_{t|t-h}^{(QR)}) - \rho(\hat{e}_{t|t-h}^{(MIDAS-QR)})] = 0, \forall\, t, \tag{21}$$

$$H_1: E[\rho(\hat{e}_{t|t-h}^{(QR)}) - \rho(\hat{e}_{t|t-h}^{(MIDAS-QR)})] > 0, \forall\, t. \tag{22}$$

If the CW statistic is statistically significant, the null hypothesis is rejected, indicating that the MIDAS-QR model outperforms the traditional QR model in nowcasting GDP growth in Indonesia.

3. RESULTS AND DISCUSSION

3.1 Descriptive Statistics of Research Variables

This section will discuss the results of the analysis of Indonesia's GDP growth. The data used is quarterly growth data at constant prices in 2010 from 2001 to 2024.

Table 1. Descriptive Statistics of Response Variables

Variable	Mean	Min	Max	Variance
GDP Growth	1.2493	-4.1900	5.0500	5.8619

The descriptive statistics for the response variable, quarterly GDP growth, are presented in Table 1. The average GDP growth over the observation period is 1.2493 percent, indicating a general trend of economic expansion. The volatility of the Indonesian economy is reflected in the range between the minimum (-4.1900 percent) and maximum (5.0500 percent) GDP growth values. Furthermore, the variance of 5.8619 percent confirms the substantial fluctuations in GDP growth during the observation period, which are influenced by internal and external factors. As visualized in Fig. 1, the quarter-to-quarter (q-to-q) GDP growth data exhibits a significant seasonal pattern, a common characteristic in Indonesian macroeconomic time series data. To mitigate potential issues arising from this seasonality, the MIDAS-QR approach employed in this study utilizes monthly indicators that are expected to capture dynamic relationships and implicitly account for seasonal variations. The visualization in Fig. 1 represents quarterly GDP growth, capturing both the overall trend and seasonal fluctuations.

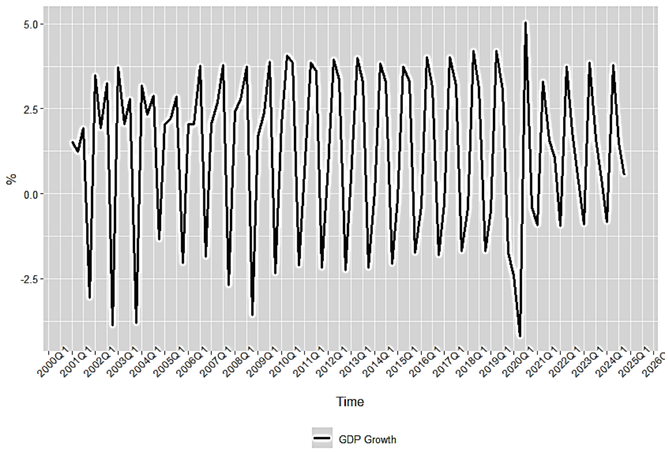


Figure 1. Response Variable Visualization

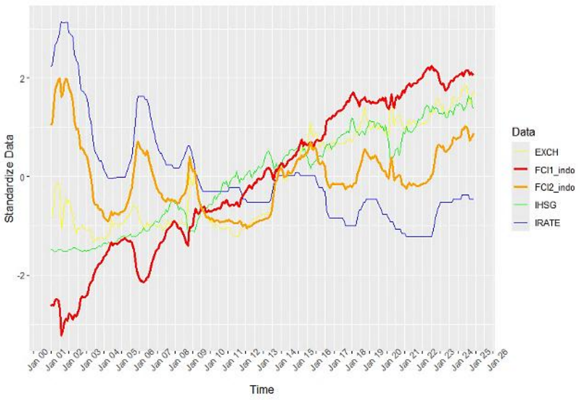
In greater detail, Fig. 1 shows a graph of Indonesia's GDP growth over time. It can be seen that this growth figure shows a fairly clear fluctuation pattern, with several sharp declines, especially in 2020 due to the COVID-19 pandemic. A seasonal pattern is also visible in the graph, indicating an economic cycle that repeats every year. After experiencing a decline, economic growth is seen to increase again, indicating that the Indonesian economy is able to recover quite quickly. This graph provides an overview of the dynamics of the Indonesian economy and can be used for further analysis, such as predictions or nowcasting.

After observing the dynamics of Indonesia's GDP growth, the next step is to analyze the predictor variables that have the potential to influence this growth. In this study, three groups of high-frequency variables were used, namely the Financial Condition Index (FCI), External Financial Environment Index (EFEI), and Macroeconomic Prosperity Leading Index (MPLI). To reduce the dimensions of these variables and avoid multicollinearity problems, Principal Component Analysis (PCA) was applied.

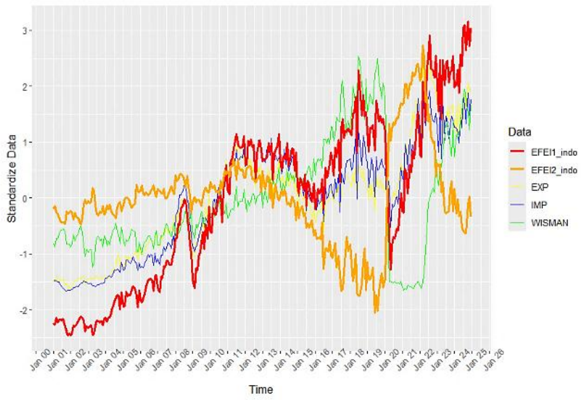
Table 2. Results of PCA FCI, EFEI, and MPLI

Variables	Importance of Components	PC1	PC2	PC3	PC4
FCI	Standard Deviation	1.5623	0.6865	0.2965	-
	Proportion of Variance	0.8136	0.1571	0.0293	-
	Cumulative Proportion	0.8136	0.9707	1.0000	-
EFEI	Standard Deviation	1.5037	0.8407	0.1791	-
	Proportion of Variance	0.7537	0.2356	0.0107	-
	Cumulative Proportion	0.7537	0.9893	1.0000	-
MPLI	Standard Deviation	1.9732	0.3185	0.0536	0.0457
	Proportion of Variance	0.9734	0.0254	0.0007	0.0005
	Cumulative Proportion	0.9734	0.9988	0.9995	1.0000

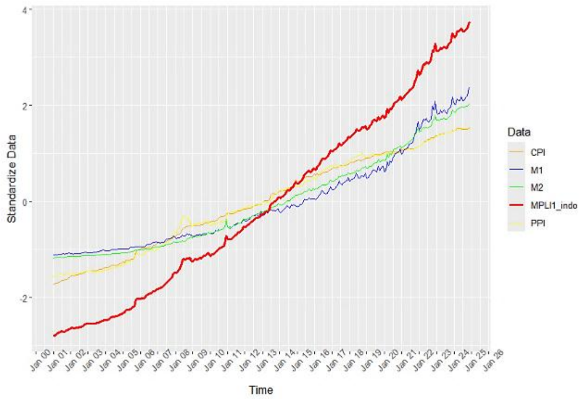
The PCA results for FCI, EFEI, and MPLI, respectively, are presented in Table 2. In accordance with the criteria for selecting the number of principal components by Wu & Qiu [25], the PCs were selected with a cumulative proportion of at least 90%. The PCA results show that for FCI, two principal components (PC1 and PC2) are able to explain 97.07% of the variance. Meanwhile, for EFEI, two principal components are also able to explain 98.93% of the variance. In MPLI, only one principal component (PC1) is sufficient to explain 97.34% of the variance. These principal components are then used as predictor variables in the MIDAS-QR model.



(a)



(b)



(c)

Figure 2. Predictor Visualization of (a) FCI, (b) EFEI, and (c) MPLI

To provide a clearer illustration of these results, Fig. 2 above shows the data movement of three groups of predictor variables, namely FCI, EFEI, and MPLI, as well as the main components of the PCA reduction results. Dynamic domestic financial conditions, reflected by sharp fluctuations in FCI data such as exchange rates (EXCH), interest rates (IRATE), and stock indexes (IHSG), are summarized by PCA into highly volatile PC1 and PC2 that follow a smoother trend. Furthermore, global conditions that affect EFEI variables such as exports (EXP), imports (IMP), and foreign tourists (WISMAN) cause volatility in the data, which are then represented by PC1 and PC2 of EFEI. Finally, the macroeconomic outlook that tends to be stable and increasing, seen in MPLI data such as CPI, M1, M2, and PPI, is consistently summarized by PC1, which shows an upward trend. In other words, the large amount of data with different patterns from each group of variables has been successfully simplified by PCA into representative main components, thus facilitating analysis and prediction in the model while maintaining important information.

3.2 Parameter Estimates of the QR and MIDAS-QR Models Formed Across Quantiles

This section presents the results of parameter estimation for the Quantile Regression (QR) and Mixed Data Sampling Quantile Regression (MIDAS-QR) models for Indonesia's GDP growth. The data used in this estimation are quarterly data, with the training period spanning from 2001Q1 to 2021Q4 and the testing period from 2022Q1 to 2024Q4. In total, the dataset comprises 96 quarterly observations, of which 84 quarters (87.5%) are allocated for training and 12 quarters (12.5%) for testing. This split ensures robust model estimation while reserving a sufficient portion of data for out-of-sample validation. Therefore, the QR and MIDAS-QR model specifications formed from the PCs of each variable are presented sequentially as follows.

$$GDP\ Growth_t(\theta) = \beta_0(\theta) + \beta_{1,1}(\theta)\frac{1}{m}\sum_{k=0}^{m-1} FCI_{1,m-k}^{(t)} + \beta_{1,2}(\theta)\frac{1}{m}\sum_{k=0}^{m-1} FCI_{2,m-k}^{(t)} \quad (23)$$

$$+\beta_{2,1}(\theta)\frac{1}{m}\sum_{k=0}^{m-1} EFEI_{1,m-k}^{(t)} + \beta_{2,2}(\theta)\frac{1}{m}\sum_{k=0}^{m-1} EFEI_{2,m-k}^{(t)}$$

$$+\beta_{3,1}(\theta)\frac{1}{m}\sum_{k=0}^{m-1} MPLI_{1,m-k}^{(t)} + \alpha_2(\theta)GDP\ Growth_{t-2}$$
$$+\alpha_3(\theta)GDP\ Growth_{t-3} + \alpha_4(\theta)GDP\ Growth_{t-4} + \epsilon_t\ ,$$

$$GDP\ Growth_t(\theta) = \beta_0(\theta) + \beta_{1,1}(\theta)\sum_{k=0}^{m-1} w_k(\boldsymbol{\delta}(\theta),d)FCI_{1,m-k}^{(t)} + \beta_{1,2}(\theta)\sum_{k=0}^{m-1} w_k(\boldsymbol{\delta}(\theta),d)FCI_{2,m-k}^{(t)} \quad (24)$$
$$+\beta_{2,1}(\theta)\sum_{k=0}^{m-1} w_k(\boldsymbol{\delta}(\theta),d)EFEI_{1,m-k}^{(t)} + \beta_{2,2}(\theta)\sum_{k=0}^{m-1} w_k(\boldsymbol{\delta}(\theta),d)EFEI_{2,m-k}^{(t)}$$
$$+\beta_{3,1}(\theta)\sum_{k=0}^{m-1} w_k(\boldsymbol{\delta}(\theta),d)MPLI_{1,m-k}^{(t)} + \alpha_2(\theta)GDP\ Growth_{t-2}$$
$$+\alpha_3(\theta)GDP\ Growth_{t-3} + \alpha_4(\theta)GDP\ Growth_{t-4} + \epsilon_t,$$

The results of parameter estimation of QR and MIDAS-QR models at various quantiles (0.05, 0.25, 0.50, 0.75, and 0.95) are shown in Table 3 and Table 4. In the estimation of the MIDAS-QR model, the values $\delta_1 = 0.5$ and $\delta_2 = 0.5$ were chosen because, based on previous trial results, this combination provides the best prediction results compared to other combinations in the range of -0.5 to 0.5 (with an interval of 0.1). These estimation results provide an overview of how the predictor variables (FCI, EFEI, and MPLI) affect GDP growth at various levels of distribution.

Table 3. Results of Parameter Estimation Using QR Model

Quantile (θ)	β_0	$\beta_{1,1}$	$\beta_{1,2}$	$\beta_{2,1}$	$\beta_{2,2}$	$\beta_{3,1}$	α_2	α_3	α_4
0.05	-1.9100	-0.1897	-0.5866	1.3016	-1.3925	-1.4780	-0.1477	-0.0302	0.8598
0.25	-0.0070	0.5326	0.2760	0.2837	-0.0686	-0.7393	-0.1196	-0.0641	0.8839
0.50	0.2977	-0.0651	-0.0517	-0.2064	0.1047	0.2514	-0.0467	-0.0435	0.9466
0.75	0.8854	-0.8356	-0.4256	-0.4667	0.0912	1.0552	-0.0917	-0.0376	0.8589
0.95	2.9771	-0.4737	0.3663	-0.7317	1.0275	1.0740	-0.3043	-0.0786	0.6285

Table 4. Results of Parameter Estimation Using the MIDAS-QR Model

Quantile (θ)	β_0	$\beta_{1,1}$	$\beta_{1,2}$	$\beta_{2,1}$	$\beta_{2,2}$	$\beta_{3,1}$	α_2	α_3	α_4
0.05	-1.4442	1.0687	0.7557	1.6582	-0.7243	-2.7756	-0.1927	-0.1471	0.8545
0.25	-0.2938	0.4007	0.2366	0.4466	-0.3609	-0.8450	-0.0860	-0.0567	0.9210
0.50	0.3692	-0.1670	-0.0900	-0.2063	0.0706	0.2958	-0.0618	-0.0369	0.9132
0.75	0.9109	-0.9782	-0.4256	-0.4640	0.1004	1.1461	-0.0989	-0.0394	0.8493
0.95	2.9444	-1.0919	-0.0765	-0.8058	0.8458	1.5892	-0.2788	-0.0618	0.5683

To further clarify the modeling process, the selection of quantiles used as prediction outputs in this study will be discussed in more detail in the section on Prediction Accuracy and Nowcasting Quarterly GDP Growth at Risk. Specifically, this selection is determined based on the model's prediction performance, which is evaluated using three main quantitative metrics, namely Quantile Mean Absolute Error (QMAE), Quantile Root Mean Square Error (QRMSE), and the Clark-West (CW) Test. Thus, the choice of quantiles is closely aligned with the model's ability to provide accurate and reliable predictions across different levels of the GDP growth distribution.

3.3 Prediction Accuracy (QMAE, QRMSE, and CW Test)

To evaluate the predictive performance of the QR and MIDAS-QR models, two main metrics are used, namely QMAE and QRMSE. In addition, the Clark-West (CW) statistical test is carried out to determine whether the MIDAS-QR model is significantly superior to the QR model in predicting Indonesia's GDP growth. This evaluation was carried out in the out-of-sample period, namely from 2022Q1 to 2024Q4, after the model was trained using data from 2001Q1 to 2021Q4.

Table 5. Results of QMAE, QRMSE and CW Test

Quantile	Method	QMAE	QRMSE	CW Statistic	*p*-value
0.05	QR	0.2774	0.2848	**2.3123*** **	0,0104
	MIDAS-QR	0.2455	0.2482		
0.25	QR	0.2354	0.2551	-6.2178	1.0000
	MIDAS-QR	0.3691	0.3863		
0.50	QR	0.1802	0.2260	**1.8733** **	0.0305
	MIDAS-QR	0.1520	0.1944		
0.75	QR	0.2553	0.2701	0.1081	0.4569
	MIDAS-QR	0.2539	0.2699		
0.95	QR	0.1788	0.1847	**2.5012*** **	0.0062
	MIDAS-QR	0.1659	0.1718		

Notes: (1) This table reports the CW test results for traditional GaR vs. mixed-frequency GaR, including the value of the CW statistic and the corresponding p-value; (2) *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively; (3) Boldface indicates that mixed-frequency GaR is significantly superior to traditional GaR.

The QMAE, QRMSE values, and CW test results for both models at several quantiles (0.05, 0.25, 0.50, 0.75, and 0.95) are presented in Table 5. In general, the MIDAS-QR model produces lower QMAE and QRMSE values at several quantiles, especially at the extreme quantiles (0.05 and 0.95), indicating that its accuracy is higher than the QR model. The CW test results also support this finding, with statistically significant values at the 0.05 quantile (CW = 2.3123, p-value = 0.0104), 0.50 quantile (CW = 1.8733, p-value = 0.0305), and 0.95 quantile (CW = 2.5012, p-value = 0.0062), indicating that MIDAS-QR is statistically superior in predicting the distribution of GDP growth in extreme areas. Building on this evidence, these results clearly demonstrate the superior predictive performance of the MIDAS-QR model over the traditional QR model, particularly in capturing the risks at the tails of the GDP growth distribution.

To provide a visual representation of the model performance, Fig. 3 shows a comparison between 0.05, 0.50, and 0.95 quantile predictions from both models with the actual GDP growth values. The black line represents the actual data, while the colored lines show the prediction results from each model. The MIDAS-QR model (especially the skyblue, green, and blue lines) shows predictions that are closer to the actual data and are able to capture turning points better than the QR model.

As illustrated in Fig. 3, each quantile serves a distinct role in assessing economic conditions. The 0.05 quantile captures extreme downside risks, representing worst-case scenarios that are crucial for policymakers to anticipate and prepare for adverse economic shocks. The 0.50 quantile reflects the median or most likely outcome, providing a baseline projection of economic growth. In contrast, the 0.95 quantile highlights upside risks, identifying periods when economic performance may exceed expectations. By jointly analyzing these quantiles, the models offer a comprehensive framework for assessing the full distribution of growth risks, enabling early detection of vulnerabilities and opportunities. This multidimensional risk assessment approach is consistent with the Growth at Risk literature, such as [7], which emphasizes the importance of capturing the entire distribution of future economic outcomes to support more adaptive and risk-sensitive policymaking.

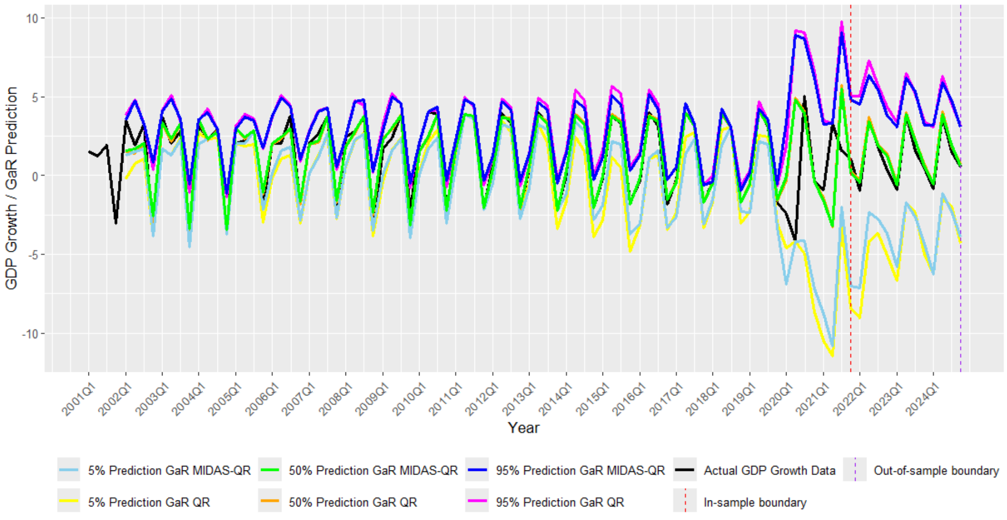


Figure 3. **Nowcasting GDP GaR 5%, 50%, and 95% Prediction Quarterly with MIDAS-QR and QR**

3.4 Nowcasting Quarterly GDP Growth at Risk

This section presents the nowcasting results of Indonesia's GDP growth for the first quarter of 2025 (2025Q1) using the MIDAS-QR model at the 95% quantile (GaR 95%). The selection of this quantile refers to the results of the previous model performance evaluation, Table 5, which showed that predictions at the upper quantile (95%) were more accurate in anticipating economic growth risks than the lower quantile (5%) and middle quantile (50%).

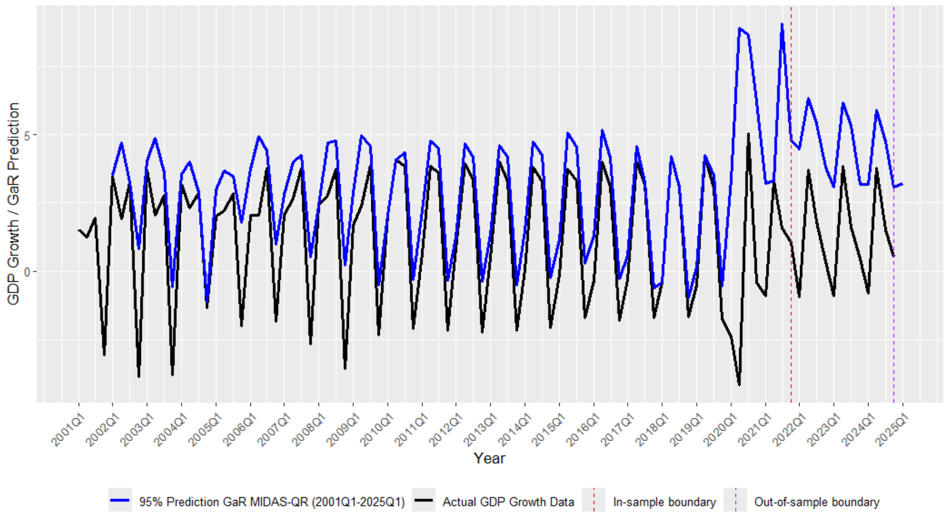


Figure 4. **Nowcasting GDP GaR 95% Quarterly based on MIDAS-QR Model**

The results of nowcasting Indonesia's quarterly GDP growth by comparing actual data and predictions of the MIDAS-QR model at the 95% quantile (GaR 95%) are presented in Fig. 4. The visualization results show that the MIDAS-QR model can capture the dynamics of GDP growth, including the sharp contraction at the onset of the COVID-19 pandemic, the subsequent recovery trend, and the potential moderation of growth indicated for 2025Q1. Therefore, these nowcasting results can function as a signal regarding the potential moderation or weakening of Indonesia's economic growth momentum in 2025Q1.

3.5 Nowcasting Monthly GDP Growth at Risk

This section presents the Growth-at-Risk (GaR) projections at a monthly frequency for the period of 2025Q1, based on the 95% GaR estimate. Fig. 5 illustrates the results of the Monthly GaR nowcasting, using the MIDAS-QR model, which indicate that risks to economic growth remain notable at the beginning of 2025. Although a recovery trend has been observed in recent years, economic uncertainty and the potential for upward risk pressures still require close monitoring.

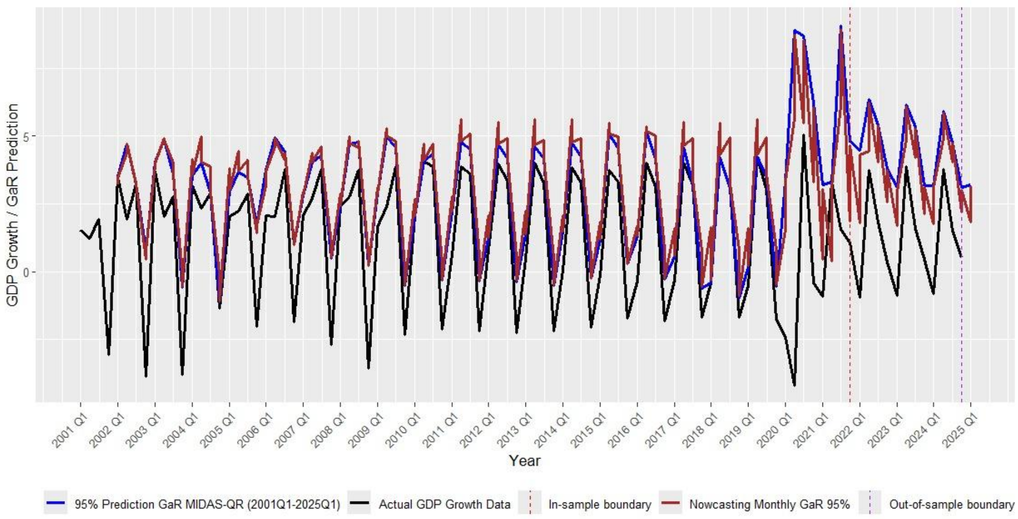


Figure 5. Nowcasting GDP GaR 95% Monthly based on MIDAS-QR Model

This monthly GaR estimate highlights the model's ability to detect dynamics in economic growth risks more promptly compared to quarterly estimates. By leveraging higher-frequency indicators, it reinforces the function of Monthly GaR nowcasting as an early-warning system prior to the release of official data, particularly in anticipating economic fluctuations driven by monthly indicators. The detailed visualization in Fig. 5 further demonstrates how the MIDAS-QR model closely tracks actual GDP growth data, capturing both downside and upside risks effectively over time. Thus, the 95% quantile Monthly GaR nowcasting plays a vital role as a real-time monitoring tool for economic risks, with a specific focus on identifying potential upside risks to Indonesia's economic growth in 2025Q1. This estimate is invaluable for guiding a more adaptive and responsive policymaking process in the face of rapidly evolving economic uncertainties, enabling timely interventions that can mitigate adverse impacts and capitalize on emerging growth opportunities.

4. CONCLUSION

This study develops the GaR approach with the MIDAS-QR model to analyze economic growth at risk and nowcast it in Indonesia. This model integrates mixed-frequency data of FCI, EFEI, and MPLI through PCA to predict economic risks across various quantiles, capturing both best- and worst-case scenarios. The mixed-frequency GaR approach significantly enhances the accuracy of predicting Indonesia's economic growth risks, both upside and downside, compared to conventional approaches. Evaluation using QMAE, QRMSE, and CW test metrics shows that the MIDAS-QR model enables early detection of potential economic downturns while providing a more comprehensive view of the GDP growth risk distribution. MIDAS-QR is also statistically superior in predicting GDP growth at the extreme quantiles and effectively capturing risks at the tails of the distribution. The empirical results demonstrate the strengths of the GaR approach with the MIDAS-QR model, showing superior out-of-sample nowcasting performance compared to the traditional GaR. This enhanced accuracy enables high-frequency monitoring of Indonesia's economic growth. Additionally, the model's nowcasting outputs serve as early signals of potential moderation or weakening in growth momentum. Overall, these findings have practical implications for policymakers of Bank Indonesia and the Ministry of Finance. Bank Indonesia can incorporate the MIDAS-QR-based GaR model into its financial stability monitoring framework to better anticipate economic stress and adjust monetary policy instruments accordingly. Meanwhile, the Ministry of Finance can utilize the model's outputs to optimize fiscal policy timing, such as government spending and revenue measures, to mitigate downside risks. By leveraging high-frequency data integration, both institutions can improve the timeliness and precision of their economic outlooks, enhancing coordination between monetary and fiscal policies in managing emerging risks. Future research may extend this framework by integrating additional high-frequency indicators, investigating alternative quantile thresholds, and leveraging machine learning methodologies to further advance the precision of risk assessments

Author Contributions

Turfah Latifah: Conceptualization, Data Curation, Formal Analysis, Funding Acquisition, Investigation, Software, Visualization, Writing - Original Draft, Writing - Review and Editing. Muhammad Sjahid Akbar: Project Administration, Supervision, Writing - Review and Editing. Dedy Dwi Prastyo: Methodology, Resources, Validation, Writing - Review and Editing. All authors discussed the results and contributed to the final manuscript.

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Declarations

The authors declare that they have no potential conflict of interest related to this study.

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