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Mixed-Data Sampling Quantile Regression (MIDAS-QR) for Nowcasting Indonesia's Economic Growth-at-Risk of Non-Oil and Gas Processing Industry Sector

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Abstract: The non-oil and gas processing industry plays a vital role in economic stability, making timely Gross Domestic Product (GDP) nowcasting essential for managing economic fluctuations and shaping effective macroeconomic policies. This study applies the Mixed Data Sampling Quantile Regression (MIDAS-QR) model to nowcast GDP growth in the non-oil and gas processing industry, a key driver of economic stability. By integrating high-frequency financial indicators, such as the Financial Stress Index (FSI) and Financial Condition Index (FCI), derived through principal component analysis, the model effectively captures non-linear patterns using an Exponential Almon Lag Polynomial function. Covering data from January 2011 to December 2023, the MIDAS-QR model demonstrates strong predictive accuracy, particularly in the electronic goods and basic metals sectors. The best performing model for nowcasting is found in the median quantile ($\tau = 0.5$), which produces the smallest error in both the electronic goods and base metals sectors. This is because the median value tends to be closer to the actual value than the other quantiles. The symmetric Mean Absolute Percentage Error (sMAPE) value in the training data for the electronic goods sector is 7.32% and testing is 9.16%, while for the base metal sector, the sMAPE value in the training data is 5.21% and testing is 4.09%. These findings enhance Growth-at-Risk (GaR) assessments, providing policymakers and industry leaders with critical insights for navigating economic uncertainties and shaping effective macroeconomic policies.

Keywords: GaR, MIDAS-QR, FCI, GDP Growth, Nowcasting

1. Introduction

In recent decades, economic growth has often been accompanied by significant uncertainty, particularly in industries that are sensitive to global and domestic market dynamics. This uncertainty is illustrated by the concept of Growth-at-Risk (GaR), which considers the distribution of future economic growth in the face of various financial and economic risks. This approach enables the measurement of systemic risks to overall economic growth and provides an important surveillance tool for economic policymakers (Xu et al., 2023).

Economic growth is one of the crucial indicators that reflect a country's economic condition over a specific period. One way to measure this economic condition is through Gross Domestic Product (GDP), which represents the added value of goods and services produced in the economy. GDP can be measured based on current prices, which describe the value added of goods and services using prices from the current year, and based on constant prices, which use prices from a specific base year as a reference to measure real growth from year to year (Sujianto, 2024). GDP at current prices can be used to observe shifts in economic structure, while GDP at constant prices is used to track economic growth from year to year.

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The most considerable contribution to Indonesia's GDP comes from the non-oil and gas processing industry sector, whose primary focus is the processing of raw materials into finished or semi-finished products that consumers or other industries can use (Fastasima et al., 2025). Data from the Ministry of Industry shows that this sector contributed the most to the national GDP, achieving 16.30% in the second quarter of 2023. The contribution of the non-oil and gas processing industry increased by 4.56% in the second quarter of 2023, surpassing the same period in 2022 by approximately 0.23 percentage points. The largest growth in the performance of the national manufacturing sector in the second quarter of 2023, specifically in the metal goods, computer, electronic goods, optical, and electrical equipment industries, increased by 17.32%, followed by the basic metal industry at 11.49%. The non-oil and gas processing industry plays a very significant role in driving the nation's economic growth because its contribution is able to provide a positive chain or multiplier effect for the economy, such as an increase in the added value of domestic raw materials, absorption of local labor, and high foreign exchange earnings from exports (Fastasima et al., 2025).

GDP data, which is a time series issued by the Central Statistics Agency (BPS), has a reasonably long release lag, occurring every three months. Hence, data publication occurs quarterly. This is due to the large scope and number of indicators that need to be calculated (Supriyatna et al., 2024). In addition, GDP data is delayed in its release by five weeks after the end of each quarter. This condition occurs at the regional and national

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levels. Of course, this long delay limits the availability of up-to-date data. In the current economic climate, where a crisis can occur at any time, the lack of real-time data can lead to delays in decision-making. This can have profound implications, especially when governments and investors need accurate and fast information to deal with economic uncertainty (Ma'Arif, 2019). Therefore, the early and high-frequency release of economic indicator data is essential for a more real-time analysis of economic developments, thereby complementing GDP data that is generally released quarterly (Eurostat, 2016). For example, trends in inflation or unemployment data can serve as an early indicator of changes in economic growth, which can be used for forecasting or nowcasting future GDP.

A common solution to the problem of data with different frequencies is to transform the data so that the dependent and independent variables have the same frequency. However, this transformation can lead to the loss of important information, making it difficult to recognize the relationship between variables. In time series regression models, all variables used should have the same frequency; therefore, data with high frequencies need to be transformed into lower frequencies. To overcome this limitation, the Mixed Data Sampling (MIDAS) regression model, introduced by Ghysels et al. (2004), is employed. MIDAS can reduce high-frequency data to a lower frequency according to the target variable without losing information from the data (Xu M et al., 2025). The reduction process is performed by assigning weights that take into account the contribution of each period, resulting in more accurate results compared to using ordinary averages. Another advantage of the MIDAS regression model is that it can minimize the number of parameters that need to be estimated, making it a simpler regression model. This model is beneficial in economic contexts where various indicators are available at varying frequencies to estimate quarterly GDP, which is typically released at a lower frequency (Kuzin et al., 2011).

This study employed a different MIDAS-QR approach compared to previous studies. Research (Utari & Rosadi, 2018) used conventional MIDAS to forecast Indonesia's GDP with JCI as a predictor, but did not consider risk distribution (quantile). Meanwhile, Research (Saputra et al., 2024) proposed a hybrid QRNN-MIDAS model for GaR, which, although sophisticated, may reduce the interpretability of the results due to the complexity of the neural network. The advantage of our study lies in combining the flexibility of MIDAS with direct quantile analysis, allowing for more efficient and interpretable GaR estimation, especially for understanding the impact of high-frequency predictors on the tail of the GDP distribution.

This study aims to obtain nowcasting results for the GDP of the non-oil and gas processing industry subsector using the MIDAS-QR model, which facilitates model specification in the presence of mixed-frequency data. By utilizing quarterly GDP data, as well as various economic indicators available at a monthly frequency, this study aims to provide more accurate GDP predictions and a deeper understanding of GDP dynamics. The results of this study are expected to contribute both academically and practically in efforts to control the GDP of the non-oil and gas processing industry sub-sector in Indonesia.

2. Literature Review

2.1 Mixed Data Sampling (MIDAS) Regression

In time series regression analysis, the data used is generally available at the same frequency. However, in this study, the regression model is formed with predictors with different frequencies. To deal with time series data that has different frequencies, a Mixed Data Sampling model is used, hereafter referred to as MIDAS regression. Unlike the autoregressive (AR) model, MIDAS regression employs predictors with varying sampling frequencies. The AR model indirectly assumes that the data is taken at the same frequency as the previous period (Ghysels et al., 2004).

Suppose $y_t, t \in T$ is the univariate response variable of a low-frequency (quarterly) observation, where t represents the quarterly time period. Meanwhile $x_m, m \in M$ are the predictor variables of high-frequency (monthly) observations, where m represents the monthly time index. In general, the mixed frequency regression model with an autoregressive lag L can be expressed in the following equation (Ghysels et al., 2016):

$$y_t = \alpha_1 y_{t-L_1} + \cdots + \alpha_L y_{t-L_J} + \beta_0 x_{mt} + \beta_1 x_{mt-1} + \cdots + \beta_{m-1} x_{m(t-1)+1} + \varepsilon_t, \quad (1)$$

which is equivalent to

$$y_t = \sum_{j=1}^{J} \alpha_j y_{t-L_j} + \sum_{k=0}^{m-1} \beta_k x_{mt-k} + \varepsilon_t, \quad (2)$$

It is important to remember that the variable x must be represented according to time t at low periods (Saputra et al., 2024). Therefore, MIDAS regression involves linear projection using the stochastic process $\{x_k^{(t)}, k \in M\}$, which is obtained from the higher frequency (monthly). At each low frequency with period t, the process $x_k^{(t)}$ will be observed at a high frequency with a period $k = (t-1)m + 1, \ldots, tm$, so Equation (1) can be rewritten as follows.

$$y_t = \alpha_1 y_{t-1} + \cdots + \alpha_L y_{t-L} + \beta_0^{(t)} x_m^{(t)} + \beta_1^{(t)} x_{m-1}^{(t)} + \cdots + \beta_{m-1}^{(t)} x_1^{(t)} + \varepsilon_t, \quad (3)$$

which is equivalent to

$$y_t = \sum_{j=1}^{J} \alpha_j y_{t-j} + \sum_{k=0}^{m-1} \beta_k^{(t)} x_{m-k}^{(t)} + \varepsilon_t \quad (4)$$

2.2 Determination of Parameters of the Weighting Function

One of the main aspects of the MIDAS regression model is the parameterization of the weight function $c(k; \boldsymbol{\delta})$. In addition, it is also important to ensure that the sum of the weight functions is one (Utari & Rosadi, 2018). Another goal of the weight function in MIDAS regression is to achieve flexibility while still maintaining the simplicity of the model.

The method of determining the parameters of the weight function used is called the Almon Exponential, as it is closely related to the Almon polynomial function. The Almon Exponential weight function is expressed as follows:

$$b(L_m, \boldsymbol{\delta}) = \sum_{k=0}^{K} c(k, \boldsymbol{\delta})\, L_m^k, c(k; \boldsymbol{\delta}) = \frac{\exp(\delta_1 k + \cdots + \delta_Q k^Q)}{\sum_{k=0}^{K} \exp(\delta_1 k + \ldots + \delta_Q k^Q)} \quad (5)$$

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The specification is parsimonious, with only two parameters to estimate, $\boldsymbol{\delta} = (\delta_1, \delta_2)'$. This aims to simplify the model while still ensuring flexibility in specifying the polynomial form. Therefore, Equation (5) can be rewritten as follows (Ghysels et al., 2005):

$$c(k; \boldsymbol{\delta}) = \frac{\exp(\delta_1 k + \delta_2 k^2)}{\sum_{k=0}^{K} \exp(\delta_1 k + \delta_2 k^2)} \quad (6)$$

2.3 Determination of Optimum Lag

Determining the optimal lag is crucial in time series analysis. This is because the effects of an economic policy generally do not have an immediate impact on economic activity at the same time, but require time or inertia for the effects to be seen. The criterion used to determine the optimum lag length is the Akaike Information Criterion (AIC). The formula for this selection criterion is (Tsay, 2010):

$$AIC = n \ln(\hat{\sigma}_\varepsilon^2) + 2\, m \quad (7)$$

with $\hat{\sigma}_\varepsilon^2 = \frac{SSE}{n}$, SSE is the Sum of Squared Error can be estimated from the sum of the squares of all error values, n is the number of observations, mIs the number of parameters estimated. The best model is the model with the smallest AIC value.

2.4 Quantile Regression (QR)

Quantile regression is a regression analysis approach introduced by Koenker and Basset in 1978 (Koenker & Bassett, 1978). A quantile regression model is proposed based on the reparameterization of the original distribution by incorporating quantile parameters (Saulo et al., 2023). Estimators in quantile regression are obtained by estimating the value of the quantile function of a distribution Y which is a function or a linear combination of X. Quantile regression can be used to explore the problem of heterogeneous data distribution (Koenker, 2017).

Suppose Y is a random variable with a cumulative distribution F_Y and τ is a natural number (probability) at a certain quantile index $0 < \tau < 1$ then the τth of F_Y can be expressed as (White & Kim, 2015):

$$Q_Y(\tau) = inf\ \{y: F(y) \geq \tau\}, \quad (8)$$

where $F_Y\ (y) = P(Y \leq y)$ is the cumulative distribution of Y. If $F(y)$ is a monotonically increasing function, then the τth quantile can be represented as:

$$Q_Y(\tau) = F^{-1}(\tau), \quad (9)$$

which can also be represented in the following way:

$$Q_Y(\tau) = \int_{-\infty}^{\infty} dF(y) = E[1\{Y \leq Q_Y(\tau)\}|\mathcal{F}_{t-1}] = \tau. \quad (10)$$

If the variable Y is affected by the covariate x, then the τth conditional quantile, which is then called quantile regression, is expressed as:

$$\hat{Q}(\tau|\mathbf{X}) = \mathbf{X}\hat{\boldsymbol{\beta}}(\tau), \quad (11)$$

So that the model for y at the τth quantile is:

$$\mathbf{y}(\tau) = \mathbf{X}\hat{\boldsymbol{\beta}}(\tau) + \varepsilon, \quad (12)$$

where $\boldsymbol{\beta}(\tau)$ are the regression model's parameters at the τth quantile and ε is the residual.

Based on the Equation (12), the vector $\boldsymbol{\beta}(\tau)$ can be estimated by $\hat{\boldsymbol{\beta}}(\tau)$ which is then called the model parameter estimate at the τth quantile. The Least Absolute Deviation (LAD) method is used to estimate the parameters in quantile regression. This method minimizes the absolute sum of the weighted residuals. The weight of the residual will be given a weight of τ if the residual ε_t is more than or equal to zero, while if the residual is less than zero, a weight of $1 - \tau$ (Koenker & Bassett, 1978). The parameter estimation can be obtained using the following equation:

$$\hat{\boldsymbol{\beta}}(\tau) = \min_{\beta} \left[\sum_{y \in \{t: y \geq \mathbf{X}\boldsymbol{\beta}\}} \tau |\boldsymbol{y} - \mathbf{X}\boldsymbol{\beta}| + \sum_{y \in \{t: y < \boldsymbol{X\beta}\}} (1-\tau)|\boldsymbol{y} - \mathbf{X}\boldsymbol{\beta}|\right], \quad (13)$$

So, the estimated value of $\hat{\boldsymbol{\beta}}(\tau)$ is obtained for each $\tau - \text{th}$. If there is an autoregressive process in the response, then Equation (13) can be written as (Koenker, 2017):

$$\hat{\boldsymbol{\beta}}(\tau) = \underset{\beta}{\operatorname{argmin}} \sum_{t=1}^{T} \rho_\tau (y_t - \mathbf{Z}_{t-h}\hat{\boldsymbol{\beta}}(\tau)), \quad (14)$$

with $\rho_\tau = \begin{cases} \tau\varepsilon_t, \varepsilon_t \geq 0 \\ (\tau - 1)\varepsilon_t, \varepsilon_t < 0' \end{cases}$ where $\mathbf{Z}_{t-h} = \left(y_{t-h}, \mathbf{X}_m^{(t-h)}\right)_{T \times (L+p)}$ with h being the forecast horizon and ε_t being the residual of the parameter estimation result. At the end, the Equation (14) becomes :

$$\hat{\boldsymbol{\beta}}(\tau) = \min_{\boldsymbol{\beta}} \left[\frac{1}{t}\sum_{t=1}^{T} \rho_\tau (y_t - \hat{y}_t(\tau))\right], \quad (15)$$

where y_t denotes the response observation with the time index $t = 1,2, \ldots, T$ (Rantini et al., 2018).

2.5 Mixed Data Sampling Quantile Regression (MIDAS-QR)

The concept of MIDAS quantile regression (MIDAS-QR) is proposed as a solution to account for high-frequency financial data in real-time financial risk measurement. There is a problem in combining high-frequency financial indicators with lower-frequency GDP data. Higher-frequency data is thought to be able to predict lower-frequency data. However, the problem lies in aggregating the high-frequency data properly. The lag structure used previously does not allow the model to respond quickly to shocks, rendering it less useful for policy purposes. Therefore, to overcome this, Ferrara et al. (2020) proposed a combined method called MIDAS Quantile Regression (MIDAS-QR), which is then defined as:

$$y_t(\tau) = \sum_{j=1}^{L} a_j(\tau) y_{t-j} + \sum_{i=1}^{p} \beta_i(\tau) \sum_{k=0}^{m-1} w_i(\boldsymbol{\delta}(\tau), k) x_{i,m-k}^{(t)} + \varepsilon_t, \quad (16)$$

where $(\boldsymbol{\delta}(\tau), k)$ is a weighting function whose sum is close to one. It depends on the polynomial parameter vector $\boldsymbol{\delta}(\tau)$ and a sequence of lags k. Note that $x_m^{(t)}$ and y_t refers to monthly and quarterly data, respectively. Using the Almon lag polynomial, we can express the Equation (16) as follows:

$$y_t(\tau) = \sum_{j=1}^{L} a_j(\tau) y_{t-j} + \sum_{i=1}^{p} \beta_i(\tau) \sum_{k=0}^{m-1} w_i(\boldsymbol{\delta}, k) x_{i,m-k}^{(t)} + \varepsilon_t, \quad (17)$$

where $w_k(\boldsymbol{\delta}, k)$ is the Almon lag weight. One type of Almon lag is the exponential Almon lag polynomial. The advantage of the Almon lag polynomial is that the Equation (17) is linear and follows the principle of parsimony as it only depends on m parameters, which are weights for high-frequency variables.

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2.6 Symmetric Mean Absolute Percentage Error (SMAPE)

The best forecasting is achieved by minimizing the error rate. The level of forecasting accuracy can be calculated using sMAPE (symmetric Mean Absolute Percentage Error). This forecasting evaluation aims to see the performance of the testing data in forecasting the time series model. sMAPE calculates a measure of error presentation with the following formula (Makridakis & Hibon, 2000):

$$\text{sMAPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{|y_t - \hat{y}_t|}{(|y_t| + |\hat{y}_t|)} \times 100\% \quad (18)$$

Table 1. Forecasting Accuracy Level Rating Scale

sMAPE	Forecasting Accuracy Level
$\leq 10\%$	Highly Accurate forecasting
$10\% < \text{sMAPE} \leq 20\%$	Good forecasting
$20\% < \text{sMAPE} \leq 50\%$	Reasonable forecasting
$> 50\%$	Inaccurate forecasting

Table 1 shows the interpretation of the results obtained with sMAPE. This table classifies the forecasting accuracy based on the sMAPE value. The lower the sMAPE value, the more accurate the forecasting, while higher values indicate less accurate forecasting (Hu et al., 2022).

3. Methodology

3.1 Research Data Source

The data used in this study were obtained from various sources as listed in Table 2. The period of data collection spans from 2011 to 2023. The data used in this study have different frequencies. The response variable is available at low frequency, which is quarterly, while the predictors are available at high frequency, which is monthly. This frequency difference reflects the varying intervals of measurement between the response variable and the predictors, which must be considered when selecting and applying the appropriate analytical methods to ensure accurate results.

3.2 Model Specifications

The model specification of the MIDAS-QR method is as follows. The MIDAS-QR model for $y_{1,t}$ (GDP Growth of Electronic Goods Industry Sector) is

$$y_{1,t}(\tau) = \sum_{j=1}^{L}\alpha_{i,j}(\tau)y_{1,t-j} + \beta_1(\tau)\sum_{k=0}^{m-1}w(\delta,k)FSI_{t-k} + \sum_{i=1}^{s}\gamma_{1,i}(\tau)\sum_{k=0}^{m-1}w(\delta^{'},k)G_{i,t-k} + \varepsilon_{1,t}(\tau).$$

The MIDAS-QR model for $y_{2,t}$ (GDP Growth of Basic Metals Sector) is

$$y_{2,t}(\tau) = \sum_{j=1}^{L}\alpha_{i,j}(\tau)y_{2,t-j} + \beta_2(\tau)\sum_{k=0}^{m-1}w(\delta,k)FSI_{t-k} + \sum_{i=1}^{s}\gamma_{2,i}(\tau)\sum_{k=0}^{m-1}w(\delta^{'},k)G_{i,t-k} + \varepsilon_{2,t}(\tau).$$

Table 2. Research Data Source

Data	Frequency	Source
GDP of the non-oil and gas processing industry subsector	Quarterly	Central Statistics Agency
FSI Global	Monthly	Office of Financial Research
EXC	Monthly	Yahoo Finance
JCI	Monthly	Yahoo Finance
CCI	Monthly	Organisation for Economic Co-operation and Development
INFL	Monthly	Central Statistics Agency
RATE	Monthly	Central Statistics Agency

3.3 Research Variables and Steps of Research

The variables used in this study comprise data consisting of 8 variables, as explained in Table 3. Figure 1 illustrates the research steps, specifically the process of obtaining the best model for nowcasting using the MIDAS-QR method, based on the data used.

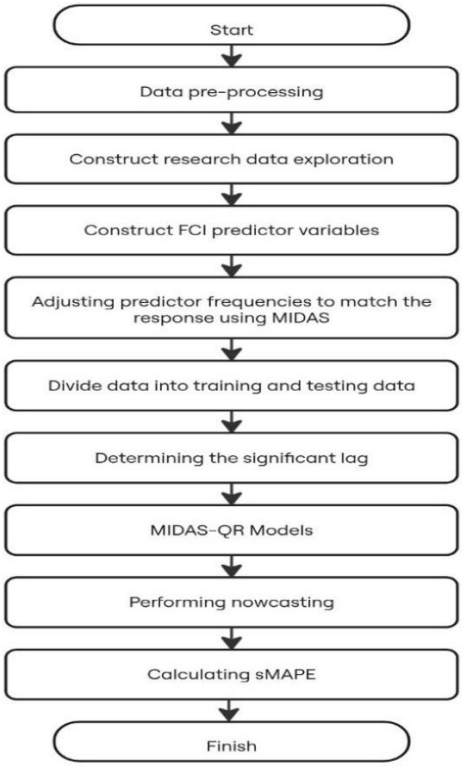


Figure 1. Step Analysis of Research

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Table 3. Research Variables

	Variables		Description
Response	$(y_{1,t})$		GDP Growth of Electronic Goods Industry Sector, etc.
	$(y_{2,t})$		GDP Growth of the Basic Metals Sector
Predictor	FSI_t $(x_{1,t})$		*Financial Stress Index*
	FCI_t (G_i) *i*=1,...,*s* *s* is the number of PCs used	EXC $(x_{21,t})$	*Exchange Rate* (USD IDR)
		JCI $(x_{22,t})$	*Jakarta Composite Index*
		CCI $(x_{23,t})$	*Consumer Confidence Index*
		INFL $(x_{24,t})$	*Inflation Rate*
		RATE $(x_{25,t})$	*Interest Rate*

4. Results and Discussion

GDP growth data are calculated based on the GDP growth rate at constant 2010 base prices. The data was collected from the first quarter of 2011 (2011Q1) to the fourth quarter of 2023 (2023Q4). This growth data is used as the response variable in MIDAS-QR modeling and is then referred to as the response.

Descriptive statistics of these response variables were calculated, with the results summarized in Table 4. These values indicate a minimum range for the variables GDP Growth of the Electronic Goods Industry Sector and GDP Growth of the Basic Metals Sector, ranging from -6.87 to 8.44 and from -13.2 to 11.55, respectively. The average growth rates were recorded at 1.15 and 2.18, while the variances were 12.12 and 22.25. These relatively small variances indicate that the data has low volatility.

Table 4. Descriptive Statistics of Response Variables

Variables	Mean	Min	Max	Varians
$y_{1,t}$	1.149038	-6.87	8.44	12.12488
$y_{2,t}$	2.181154	-13.2	11.55	22.24781

To provide further visualization, the response variable is visualized in the form of a time series plot, as shown in Figure 2.

The first exogenous predictor variable used in MIDAS-QR modeling in this study is the Financial Stress Index (FSI). Data for the FSI is obtained from the Office of Financial Research, which presents an aggregated index to measure the level of financial stress in an economy. The index encompasses four major financial markets: the banking market, the foreign exchange market, the equity market, and the debt market. The FSI data is collected at a monthly frequency to reflect current market dynamics. The movement pattern of the FSI value during the study period is visualized in Figure 3.

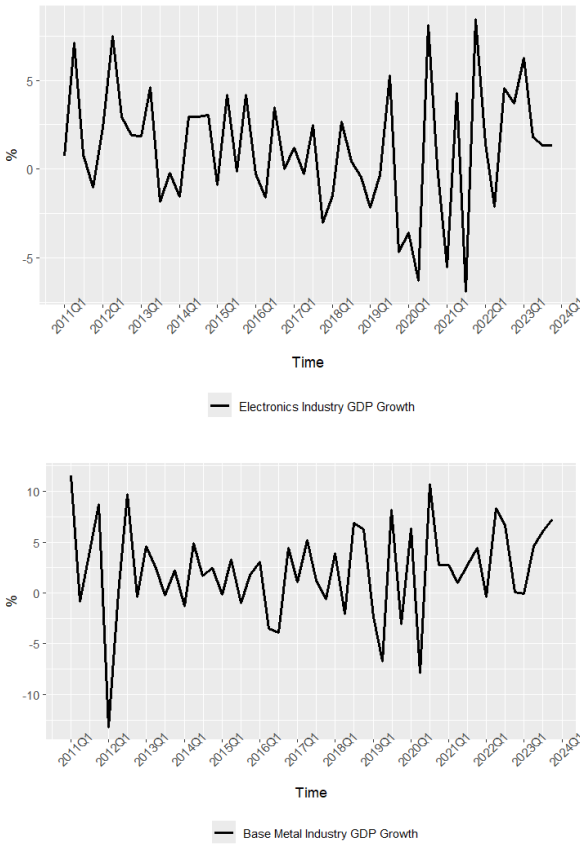


Figure 2. Indonesia GDP Growth Data

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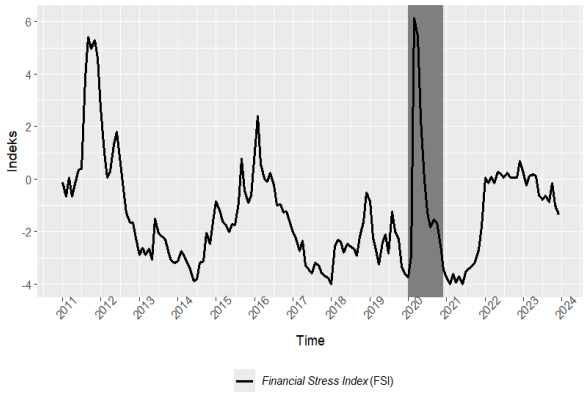


Figure 3. The FSI Time Series Plot

Based on Figure 3, it can be seen that the FSI index experienced significant fluctuations in specific periods, especially when economic conditions faced severe pressure. One example occurred from 2020 to 2021, which is characterized by the impact of the COVID-19 pandemic. This period was characterized by a sharp spike in FSI values, as shown in the black-marked area. The COVID-19 pandemic, which began in early 2020, placed tremendous pressure on the global economy, including that of Indonesia, by significantly impacting major financial markets. This pattern illustrates the high economic instability during the pandemic.

The abnormal pattern in FSI values during the COVID-19 pandemic period reflects the disruptions that have occurred in various economic sectors. Such instability is also evident in the graph, which shows a spike in the index value from 2020 to early 2021. The movement of the FSI during this period provides important insights to understand the impact of the pandemic on financial stress and overall economic conditions.

The second exogenous predictor variable, the Financial Conditions Index (FCI), is one of the primary indicators that reflect a country's financial condition. In this study, the FCI is calculated using the Principal Component Analysis (PCA) approach, which allows the extraction of information from various high-frequency financial variables, as depicted in Table 3, to form a composite index that represents overall financial conditions. The following is the process of forming FCI variables through the PCA process.

The PCA results indicate that there are five primary components (PC1, PC2, PC3, PC4, PC5) that account for the variability in the financial data used to construct the FCI. Based on the cumulative value of variance, the main component selection criteria must be able to explain at least 80% of the information in the data. In Table 5 above, three main components (PC1, PC2, and PC3) are identified in the formation of the composite index (FCI), as they account for 81.28% of the total relevant information.

The following is a visualization plot of the relationship between the FSI and FCI, which illustrates the relationship between the two indices more clearly and comprehensively. The relationship between FSI and FCI can be seen from the Figure 4. When financial market pressure, as represented by FSI, decreases, financial conditions, as measured by FCI, tend to improve; conversely, when financial market pressure increases,

Table 5. Results of PCA for FCI

	PC_1	PC_2	PC_3	PC_4	PC_5
Standard Deviation	1.4426	1.0416	0.9477	0.7188	0.64760
Proportion of Variance	0.4162	0.2170	0.1796	0.1033	0.08388
Cumulative Proportion	0.4162	0.6332	0.8128	0.9161	1.00000

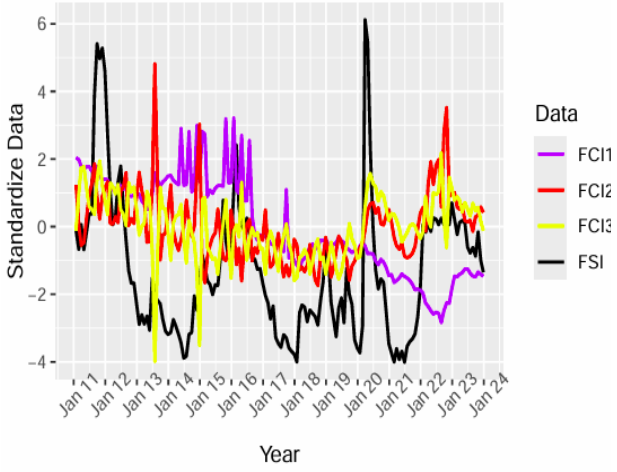


Figure 4. Illustration of the relationship between the Financial Stress Index and the Financial Condition Index

financial conditions also worsen. One of the significant events reflected in the graph is the impact of the COVID-19 pandemic, which occurred from late 2019 to 2020, as seen in the spike in FSI. The pandemic caused an increase in economic pressure, leading to a decline in financial conditions, which was reflected in the decrease in the FCI value. However, after the pandemic ended in 2021, there was a significant recovery as reflected in the increase in FCI1, FCI2, and FCI3, indicating an economic recovery followed by an improvement in financial conditions.

The choice of lag length used in this study refers to the lag interval ranging from lag 1 to lag 4 for each GDP sector, which corresponds to the data structure that divides 1 year into 4 quarters. Thus, the model accommodates the pattern of data changes between quarters in each year. The optimum lag test is shown in Table 6.

Based on Table 6, regarding the optimum lag test, the lag selection for each sector is determined by the smallest Akaike Information Criterion (AIC) value, indicating the most efficient model. In the Electronic Goods Industry sector and similar fields, the optimum lag is located at lag 1, with an AIC value of -3.097, which is the smallest value among lags 2 to 4. Meanwhile, for the Basic Metals sector, the optimum lag is at lag 2 with an AIC value of -25.119, which is lower than lags 1, 3, and 4. The selection of these lags is based on the principle that the smaller the AIC value, the better the model is at balancing accuracy and complexity. Thus, lag one is used for the Electronic Goods Industry sector and

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lag 2 for the Basic Metals sector in the MIDAS-QR model analysis. Furthermore, the MIDAS-QR model is used to analyze the relationship between response and predictor variables at different quantiles. The model is applied to two main sectors: the GDP for the Electronic and Similar Goods Industry Sector and the GDP Growth of the Basic Metals Sector.

Table 6. Optimum Lag test

Variables	*Lag*	AIC
y_1	1	-3.097*
	2	-1.171
	3	0.811
	4	2.089
y_2	1	-24.937
	2	-25.119*
	3	-23.326
	4	-21.760

**lag* optimum

The MIDAS-QR model for the GDP of the Electronic and Similar Goods Industry Sector is presented in various quantiles as follows:

$$\hat{y}_{1,t}(0.05) = 0.225 - 0.193PDB_{L1,t-1} - 0.078.FSI_{t-1} + 0.601.FCI_t - 0.009.FCI2_t - 0.305FCI3_t$$
$$\hat{y}_{1,t}(0.50) = 0.331 - 0.232.PDB_{L1,t-1} - 0.143.FSI_{t-1} + 0.105.FCI_t + 0.374.FCI2_t + 0.228.FCI3_t$$
$$\hat{y}_{1,t}(0.95) = 0.761 - 0.512.PDB_{L1,t-1} + 0.368.FSI_{t-1} - 0.009.FCI_t + 0.030.FCI2_t + 0.249.FCI3_t$$

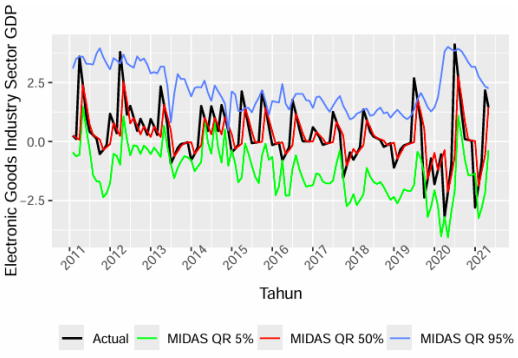
Furthermore, the MIDAS-QR model is also applied to the Basic Metals Sector GDP Growth sector at various quantiles as follows.

The MIDAS-QR model shows how various economic variables affect the growth of the electronic goods industry and the base metals sector at different levels of data distribution. The model offers a more comprehensive understanding of how macroeconomic factors impact these industry sectors under diverse economic conditions.

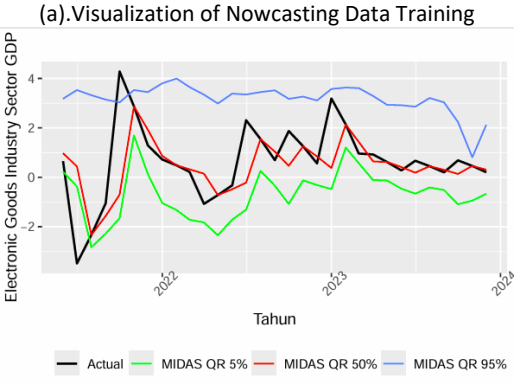
$$\hat{y}_{2,t}(0.05) = 0.716 - 0.674.PDB_{L1,t-1} - 0.409.PDB_{L2,t-2} - 0.670.FSI_{t-1} - 0.339.FCI_t + 0.120.FCI2_t + 1.031.FCI3_t$$
$$\hat{y}_{2,t}(0.50) = 1.066 - 0.656.PDB_{L1,t-1} - 0.236.PDB_{L2,t-2} - 0.094.FSI_{t-1} - 0.129.FCI_t + 0.260.FCI2_t + 0.194.FCI3_t$$
$$\hat{y}_{2,t}(0.95) = 1.447 - 0.523.PDB_{L1,t-1} - 0.359.PDB_{L2,t-2} + 0.138.FSI_{t-1} - 0.155.FCI_t + 0.090.FCI2_t - 0.171.FCI3_t$$

Table 7. Accuracy of Nowcasting Results on Training and Testing Data

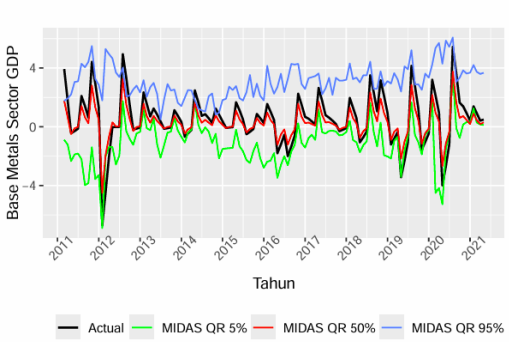
$\tau = 50\%$	
sMAPE *Training* (%)	sMAPE *Testing* (%)
7.32	9.61
5.21	4.09



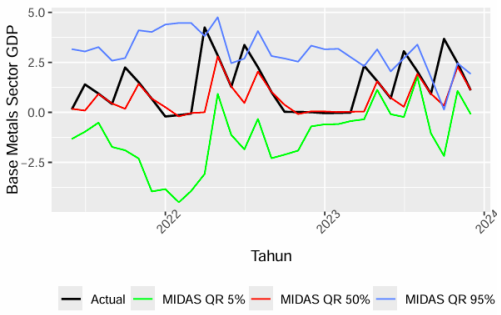
(a).Visualization of Nowcasting Data Training



(b). Visualization of Nowcasting Data Testing



(c). Visualization of Nowcasting Data Training



(d). Visualization of Nowcasting Data Testing

Figure 5. Visualization of Nowcasting Data for Training and Testing MIDAS-QR Model

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Based on the calculation results, the following table and graph illustrate the performance of the MIDAS-QR model in predicting the GDP growth of the electronic goods industry sector and the basic metals sector, considering various quantiles.

Table 7 compares the sMAPE (Symmetric Mean Absolute Percentage Error) values on the training and testing data for each sector at $\tau = 50\%$. In the GDP of the electronic goods industry sector, the training sMAPE value is 7.32% and the testing sMAPE is 9.61%, indicating that this model has a relatively small prediction error when applied to both training and testing data. In the GDP of the basic metal sector, the sMAPE values for training and testing are 5.21% and 4.09%, respectively, indicating that this sector model has higher accuracy than the electronic goods industry sector. The accuracy of this model is improved, as reflected in the relatively lower sMAPE value. Based on Table 1, the assessment of forecasting accuracy level, as indicated by the sMAPE value, reveals that all sectors fall into the highly accurate category, as the sMAPE for each sector is below 10%.

Based on Figure 5 for the training period, it can be seen that the nowcasting results using MIDAS-QR have the advantage of capturing various levels of quantile distribution, especially for GDP growth, which has high volatility. It can be seen that the prediction for the quantile 0.05 (downside risk) yields a lower prediction, while the prediction for the quantile 0.95 (upside potential) yields a higher prediction. The median prediction of 0.5 is closer to the actual line, reflecting the median or more general expectation. In the electronic goods industry sector, the 0.95 quantile is able to capture extreme spikes more effectively than the 0.5 quantile, which is centered only on the middle value. In the base metals industry sector, the MIDAS-QR model, at a quantile of 0.05, provides some points where the downside prediction offers insight into how the sector could face a sharp decline under adverse conditions. However, these downside predictions remain relatively stable in some periods. At the 0.5 quantile, the predictions at this quantile give an idea of the expected normal conditions. The graph shows that the median prediction follows a good trend with the actual data; however, there are differences at some points with large fluctuations. Meanwhile, the 0.95 quantile indicates the upside potential, representing the most optimistic prediction with the highest value in the distribution. The large spikes in the electronic goods industry and basic metal industry seen in 2020 indicate an extraordinary event, such as a COVID-19 event.

Unlike traditional linear regression, which focuses only on the mean, quantile regression allows us to predict different points across the distribution of the target variable. This provides significant advantages in capturing more detailed information about the data distribution, especially in the face of extreme fluctuations and higher uncertainty, which traditional linear regression often struggles to capture, as it only examines the mean.

MIDAS-QR model on testing data for two sub-sectors of the non-oil and gas processing industry, namely electronic goods and basic metals. The model generally follows the seasonal patterns and trends of actual data quite well, although there are some deviations, especially in extreme fluctuations, as indicated by the striking difference between the actual line and the extreme quantile limits.

5. Conclusions

This study applies the MIDAS-QR model for nowcasting GDP growth in the non-oil and gas processing industry. By integrating high-frequency financial indicators such as FSI and FCI through PCA, the GaR model is evaluated. The model proved to be effective in capturing non-linear growth patterns by using the Almon Lag Exponential polynomial function. The results show that the model provides accurate predictions, especially in the electronic goods and base metals sectors, with the best performance achieved at the median quantile ($\tau = 0.5$), which results in the smallest error.

However, this study has several limitations, including data limitations and frequency differences between the response and predictor variables, which may impact the results. Therefore, further research can consider applying the MIDAS-QR model using weighting functions other than the Almon Exponential, such as the Beta weighting function, as well as increasing the frequency of variables in both the response and predictor to improve model accuracy.

The findings from this study provide policymakers and industry leaders with important insights for addressing economic uncertainty and developing effective macroeconomic policies. For future research, it is recommended to test this model on other sectors or by using a broader dataset to gain deeper insights. This research is also expected to provide policymakers with guidance on designing more effective policies to address economic uncertainty.

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