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COMPARATIVE ANALYSIS OF TWO-STEP AND QUASI MAXIMUM LIKELIHOOD ESTIMATION IN THE DYNAMIC FACTOR MODEL FOR NOWCASTING GDP GROWTH IN INDONESIA

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ABSTRACT

Economic activity data is needed quickly to make policy decisions, but this data suffers from publication delays. Gross Domestic Product (GDP) data is released within five weeks after the end of the quarter. An effort that can be made to provide such data is through nowcasting, which is forecasting in the current period using variables that have a higher frequency. This study aims at nowcasting GDP growth. The nowcasting method used is the Dynamic Factor Model (DFM) with Two Step (TS) and Quasi Maximum Likelihood (QML) estimation. The nowcasting results show that the DFM-TS model is better than the DFM-QML because it has a larger adjusted R-squared value and has the smallest RMSE value of 1.71035 compared to the DFM-QML value, which has an RMSE value of 1.71598.

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1. INTRODUCTION

Macroeconomics is a branch of economics that studies overall economic phenomena, including inflation, unemployment, and economic growth. Macroeconomic analysis is critical in economic policymaking because of the significant impact of changes to various economic sectors. One of the leading indicators in macroeconomic analysis is the Gross Domestic Product (GDP), which is the goods and services produced by a specific region in a certain period [1]. GDP is used to measure a country's economic health and is a benchmark for evaluating economic performance. Therefore, the economic growth of a country can be indicated by an increase in the value of the country's gross domestic product (GDP) [2].

Economic development in Indonesia is influenced by three main macroeconomic variables: GDP, inflation, and the unemployment rate. Based on the advanced release calendar, the Central Bureau of Statistics (BPS) releases GDP data every quarter, inflation data every month, and unemployment rate data every May and November. Macroeconomic data released by BPS has a lag. For example, the current month's inflation will be released the following month, the February 2018 unemployment rate will be released on May 7, 2018, and the August 2018 unemployment rate will be released in November 2018. Meanwhile, GDP for the first quarter of 2018 was released by BPS on May 7, 2018; the second quarter of 2018 was released on August 6, 2018; and the third quarter of 2018 was released on November 5, 2018. Unemployment rate data has a lag of almost nine weeks, while GDP has a lag of five weeks [3].

The rapid availability of regional macroeconomic data has limitations in its collection and processing time. Economic growth data experienced a delay in its release for five weeks from the end of the quarter. This condition occurs at the national and regional levels [4]. GDP growth is one of the time series data. Time series data is a set of data that has a sequence of time-oriented or chronological observations on the variables of interest [5]. Due to the importance of up-to-date GDP data, it is necessary to forecast the current economic conditions so that efforts can be made to fulfill these data needs through nowcasting. Nowcasting is a developed form of forecasting current conditions with the principle of using higher-frequency variables. In a sense, if nowcasting is done on quarterly variables, the variables used can be monthly, weekly, or daily. Nowcasting is a method to estimate current economic conditions using the latest available data. In contrast to forecasting, which usually projects future conditions, nowcasting focuses on more accurate current estimates because it uses more up-to-date information [2]. Nowcasting is particularly useful when economic data changes rapidly, and policies must be made based on the most up-to-date conditions. For example, in an economic crisis, nowcasting can provide a clearer picture of current conditions than forecasting, which is often less responsive to rapid changes.

To obtain nowcasting results quickly and accurately, data capable of being released quickly with a high frequency is required as an estimator. One of the latest methods that can utilize estimation from high-frequency data is the Dynamic Factor Model (DFM). DFM is a statistical method that can handle datasets with large numbers and frequencies by extracting the common information shared by a group of indicators and summarizing them into a smaller set of factors [6]. [7] conducted nowcasting of economic conditions in Europe using the DFM method and several Machine Learning methods, including Regularized Regression Methods, Support Vector Machines, Random Forest, and Neural Networks. The study showed that DFM and Machine Learning methods are better than autoregressive models, where DFM excels when the data trend is normal, and machine learning methods excel in determining the turning point of a trend.

In the context of nowcasting, the use of DFM in this study becomes very relevant because DFM can capture the dynamic relationship between various economic variables. Exports contribute to GDP by generating national income. However, they are susceptible to external factors like global trade policies, which can introduce volatility; consumer goods imports indicate domestic demand for foreign products, potentially impacting local production. Capital goods and raw materials imports reflect domestic investment levels but may also signal dependency on foreign inputs; CPI reflects consumer inflation, while WPI reflects wholesale inflation. Both indices provide a comprehensive view of inflation pressures, though high inflation can erode purchasing power, affecting GDP negatively. A higher money supply can boost spending and investment, yet excessive growth without output increases could lead to inflation, affecting economic stability, and the exchange rate impacts trade competitiveness. While depreciation may boost exports, it also raises import costs, which could strain sectors dependent on foreign materials., thus providing a more comprehensive estimate. Therefore, this research is focused on forecasting quarterly GDP growth to meet the needs of economic growth data in Indonesia by using the DFM method to calculate GDP growth forecasts for each quarter in real time. DFM-TS and DFM-QML are particularly effective for nowcasting, which is essential in this study to estimate GDP growth in near-real-time despite data publication lags. Using high-frequency indicators, these methods can provide timely GDP estimates, which is valuable for policymakers who require updated economic insights.

2. RESEARCH METHODS

The research methodology consists of detailed explanations regarding the research structure, including data sources, descriptions of variables, and data analysis methods.

2.1 Data Sources

The data used in this research is secondary data sourced from BPS (Central Bureau of Statistics) in the period first quarter 2010-first quarter 2024 [8].

2.2 Research Variable

This study uses one response variable and thirteen predictor variables identified as potential factors influencing Indonesia's GDP. These variables include key economic indicators such as exports, imports, price indices, and financial and monetary data. Data are collected from various reliable sources with frequencies that vary according to the characteristics of each variable. Table 1 lists the variables used in this analysis and their descriptions, data collection frequency, and sources.

Table 1. Variable

No.	Variable	Description	Frequency	Source
1	Y	Indonesia's GDP	Quarterly	BPS
2	X1	Exports	Monthly	Ministry of Trade
3	X2	Import of Consumer Goods	Monthly	Ministry of Trade
4	X3	Import of Capital Goods	Monthly	Ministry of Trade
5	X4	Import of Raw Materials	Monthly	Ministry of Trade
6	X5	Consumer Price Index	Monthly	BPS
7	X6	Wholesale Price Index	Monthly	BPS
8	X7	Composite Stock Price Index	Monthly	Yahoo Finance
9	X8	Narrow Money Supply (M1)	Monthly	BPS
10	X9	Broad Money Supply (M2)	Monthly	BPS
11	X10	BI-Rate	Monthly	Bank Indonesia
12	X11	Rupiah Exchange Rate to USD	Monthly	BPS
13	X13	Number of Tourist Arrivals	Monthly	BPS

2.3 Analysis Technique

DFM was originally developed by [9] and [10] to estimate models using frequency-domain methods. The DFM is based on a common factor of stationary monthly indicators that can change to match the number of quarters observed at the quarter's end. The model is based on the process of transforming monthly indicators into a common factor [11]:

$$\boldsymbol{x_{i,t} = \mu + \lambda_{i1} F_{1,t} + \lambda_{i2} F_{2,t} + \cdots + \lambda_{ij} F_{j,t} + \cdots + \lambda_{jr} F_{r,t} + \zeta_{i,t}}$$

where:

$\boldsymbol{\mu}$: Constant

$\boldsymbol{x_{i,t}}$: A vector of equal number of predictor variables

$\boldsymbol{\lambda_{ij}}$: Loading factor matrix of size

$\boldsymbol{F_{j,t}}$: Common factor vector formed of size

$\boldsymbol{\zeta_{i,t}}$: Idiosyncratic component matrix of size

$\boldsymbol{r}$: Number of common factors formed

n : Number of predictor variables

Common components and idiosyncratic components are two unobserved stationary processes. The common component process is assumed to be a linear function of several common factors with $r < n$. The common factor is capture almost all movements in the constituent variables. The common factor is a vector autoregression process of order p or VAR (p)[12][13],

$$\boldsymbol{F}_t = \sum_{i=1}^{p} \boldsymbol{A_i} \boldsymbol{F}_{t-1} + \boldsymbol{U}_t$$

with:

$\boldsymbol{A_i}$: VAR (p) process coefficient matrix of size $r \times r; i = 1, 2, \ldots, p$

$\boldsymbol{U}_t$: Vector of white noise errors from the VAR(p) process.

Suppose the DFM model is rewritten in matrix notation, it will be as follows:

$$x_t = \boldsymbol{\mu} + \boldsymbol{\lambda F_t} + \boldsymbol{\zeta_t}$$

with:

$x_t = (x_{1t}, x_{2t}, \ldots, x_{nt})$

$\mu = (\mu_{1t}, \mu_{2t,\ldots,}, \mu_{nt})$

$F_t = (F_{1t}, F_{2t}, F_{nt})$

$\xi_t = (\xi_{1t}, \xi_{2t,\ldots,}, \xi_{nt})$

λ = a matrix of size "$n \times r$" containing loading factors

The GDP growth nowcasting process can be said to follow a linear function of the common factor, which can be expressed as follows[14][15]:

$$\boldsymbol{y_t} = \boldsymbol{\beta' F_t} + \varepsilon_t$$

with the ordinary least square method, the estimation for $\boldsymbol{\beta}$ i.e.:

$$\widehat{\boldsymbol{\beta}} = \left(\widehat{\boldsymbol{F}}'_t \widehat{\boldsymbol{F}}_t\right)^{-1} \widehat{\boldsymbol{F}}'_t \boldsymbol{y}_t$$

Each common factor formed is independent of each other so that it can form a full rank matrix. Thus $\left(\boldsymbol{F}_t'\boldsymbol{F}_t\right)^{-1}$ the inversion process is possible. The following are the steps used in this research:

a. Define variables on data.

b. Data stationarity testing uses the Phillips-Perron test statistic, and when variables are not stationary, variable differencing will be carried out. Divide training and testing data.

c. Constructing a common factor based on the Principal Component values.

d. Regressing common factors and response variables with the OLS Estimation method.

e. Perform nowcasting with the method and calculate MAD, RMSE, and MAPE Comparing MAD, RMSE, and MAPE of the DFM estimation model with TS and DFM model with QML.

f. Make a conclusion.

3. RESULTS AND DISCUSSION

3.1 Descriptive Analysis

Descriptive statistics from this research are presented in Table 2.

Table 2. Descriptive Statistics of Research Variables

Variable	Mean	Deviation Standard	Minimum	Maximum
X1	15964	3740	9650	27929
X2	1258.7	343.6	625.4	2490.5
X3	10960	2201	6110	17015
X4	2497.4	534.1	1393.7	3904.4
X5	113.29	13.80	88.26	139.07
X6	148.03	31.05	103.04	212.01
X7	5335.2	1159.8	2549.0	7316.1
X8	1336418	612989	490084	2675333
X9	5128486	1953216	2066481	8888400
X10	5.6681	1.2793	3.5000	7.7500
X11	12726	2271	8508	16367
X12	783441	368487	35492	1547231

Based on **Table 2**, all indicators have a fairly large data distribution. The highest variance is in the broad money supply variable (M2) (X9). Meanwhile, the indicator that has the smallest data distribution is BI-Rate (X10).

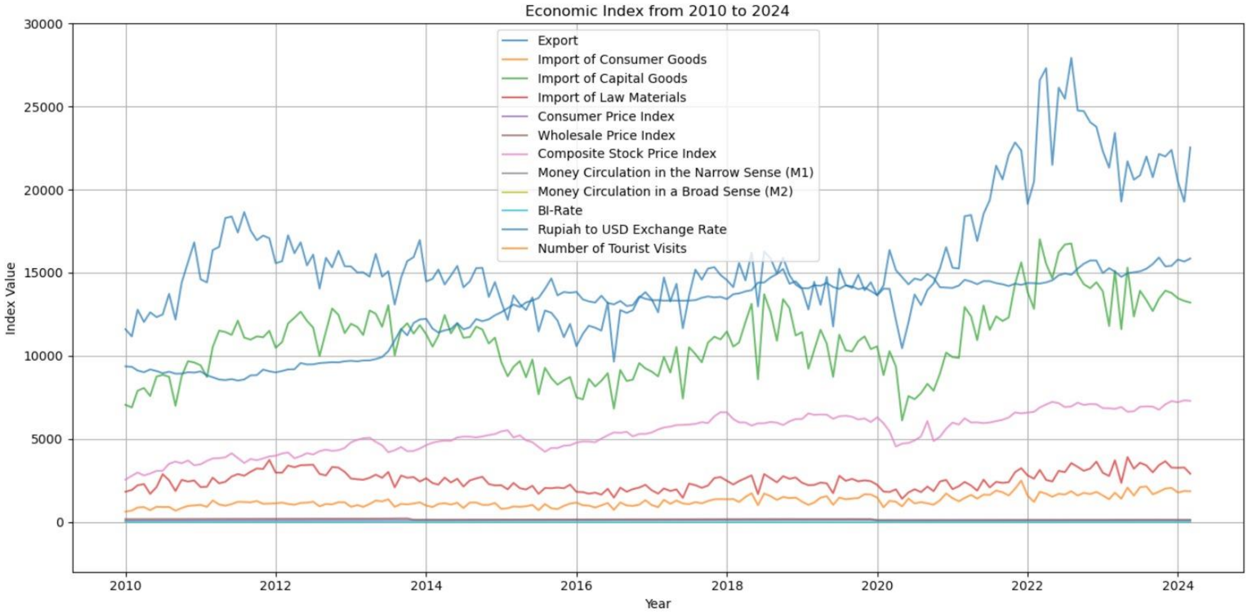

Figure 1. Index Value

Based on **Figure 1**, the movement of predictors has a pattern of movement of indicators classified as varied, which shows different responses to economic movements.

3.2 Stationarity Testing

The requirement for a predictor variable to be involved in DFM analysis is that it is already in stationary form. In this study, the stationary that is used as a requirement is stationary in the average, and differencing is done twice so that the data is stationary. The method used to test stationarity is the Phillips-Perron test, commonly called the pp-test. A stationarity test is conducted on the training period predictor data. The results of the stationarity test can be seen in the following table.

Table 3. Stationarity Test of Predictor Variables after Differencing for Two Times

No.	Variable	p-Value	Result
1	X1	<0.01	Stationer
2	X2	<0.01	Stationer
3	X3	<0.01	Stationer
4	X4	<0.01	Stationer
5	X5	<0.01	Stationer
6	X6	<0.01	Stationer
7	X7	<0.01	Stationer

No.	Variable	p-Value	Result
8	X8	<0.01	Stationer
9	X9	<0.01	Stationer
10	X10	<0.01	Stationer
11	X11	<0.01	Stationer
12	X12	<0.01	Stationer

The twelve variables are the predictor variables involved in forming the Dynamic Factor Model. Based on **Table 3**, it can be concluded that all predictor variables are stationary on average, so that they will be used in the nowcasting process.

3.3 Common Factor Formation

The first thing to do is to determine the optimum lag (p) to determine the number of lags of each predictor variable in the DFM process. In this study, the determination of the optimum lag will use four criteria, including Akaike's information criterion (AIC), Hannan-Quinn information criterion (HQ), Schwarz criterion (SC), and Final Prediction Error criterion (FPE). In each of these criteria, the optimum lag is the lag that has the smallest value.

Tabel 4. Optimum Lag Selection Results

Criterion	Lag Optimum
AIC	1
HQ	1
SC	1
FPE	1

Based on **Table 4**, since the scores of the four criteria are the same, the optimum lag used in this study can be as much as 1. After determining the optimum lag, it is necessary to decide on the number of common factors. The number of common factors (r) formed greatly influences the estimation results. The formation of the factor is expected to be able to group the values of several response variables according to the similarity of their characteristics. Determining the number of common factors uses the information criterion that minimizes the variance of the idiosyncratic component (ICr) and the eigenvalue that shows the amount of variation that can be explained in each common factor.

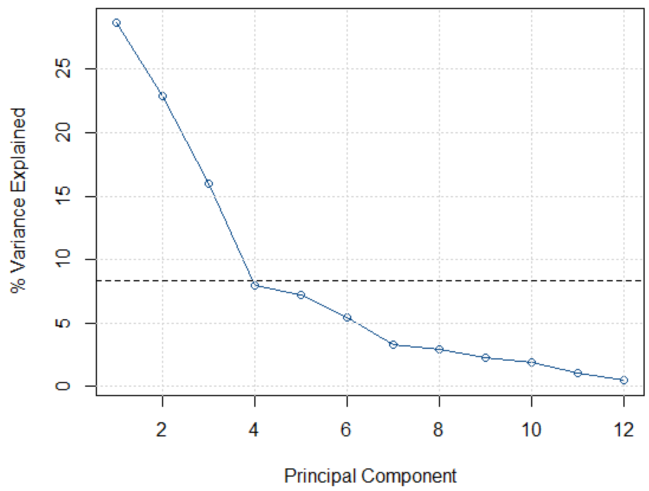

Figure 2. Scatterplot Principal Component

Based on **Figure 2**, the principal component (PC) with a high ability to explain data variation is the first three PCs. Furthermore, the DFM model will be estimated with the optimum lag (p) and the number of common factors (r) where p = 1 and r = 3. Common factors formed can be seen in **Figure 3**.

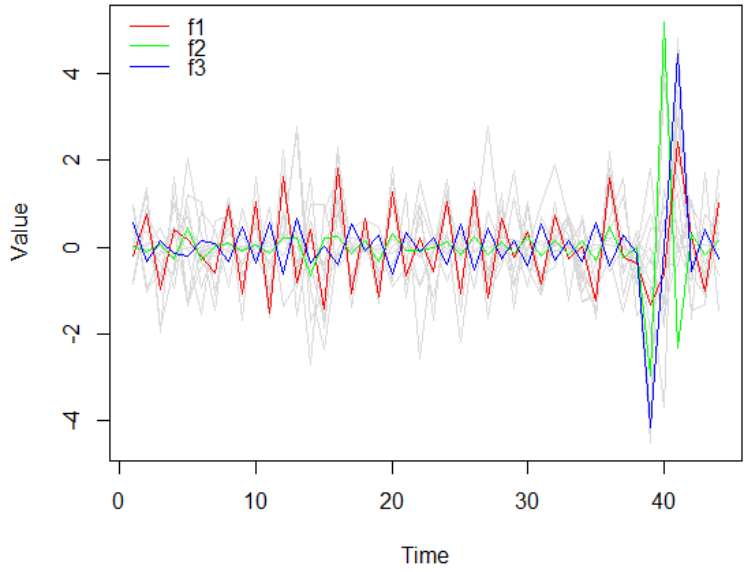

Figure 3. **Common Factor**

Based on **Figure 3**, the grouping of 12 predictor variables in the form of time series data into three common factors that are dynamic over time. With this grouping, the economic growth process is expected to be simplified even though the predictor variables have a large number. Based on the PC, each common factor consists of variables that can be seen in Table 5.

Table 5. **Variable Allocation on Each Common Factor**

Variable		
PC1	PC2	PC3
Export (X1) Import of Consumer Goods (X2) Import of Capital Goods (X3) Import of Raw Materials (X4) Money in circulation in the narrow sense (X8) Broad Money (X9) BI-Rate (X10)	Rupiah to USD Exchange Rate (X11) Number of Tourist Visits (X12)	Consumer Price Index (X5) Wholesale Trade Price Index (X6) Composite Stock Price Index (X7)

Because the data used in this modeling is from the training period, the common factor formed only exists during the training period. The common factor value will be used for the next stage of analysis.

3.4 Regression of Common Factor on Economic Growth

After the common factor is obtained from DFM modeling on the training period data, the value of each common factor will be regressed on economic growth using the Ordinary Least Square (OLS) method on both models, namely DFM-TS and DFM-QM. Economic growth will be regressed on the common factor resulting from DFM using either two-step estimation (DFM-TS) or quasi-maximum likelihood estimation (DFM-QML). The basic model of both types of estimation will be the same because the number of optimum lags and factors formed is the same. The DFM model is as follows.

$$Y_t = \beta_0 + \beta_1 F_{t,1} + \beta_2 F_{t,2} + \beta_3 F_{t,3} + \varepsilon_t$$

where:

F_t : DFM common Factor

j : Index common factor, $j = ,2,3 \dots r$

The economic growth nowcasting process is operated based on the above equation which is an OLS regression on the DFM model. The first method used is DFM-TS. The regression results can be seen in the following table.

Table 6. **OLS Regression Results on DFM-TS Model**

Estimator	**Partial**				**Simultaneous**	
	Coefficient	**t-statistic**	**p-value**	**Decision**		
Intercept	1.202046	3.608	0.000848	Significant	RSE	2.21
$F_{t,1}$	-0.772574	-3.975	0.000287	Significant	Adj R-squared	0.25631

Estimator	Partial				Simultaneous	
	Coefficient	t-statistic	p-value	Decision		
$F_{t,2}$	-0.370432	-1.686	0.099595	Not Significant	F-Statistic	6.117
$F_{t,3}$	-0.004978	-0.018	0.985786	Not Significant	P-value	000015
					Decision	Significant

Based on **Table 6**, only the first common factor is significant to economic growth, while the other 2 are insignificant. However, the three common factors will still be used as predictors in nowcasting because they simultaneously affect economic growth significantly, which can be seen from the p-value < 0.01. With the regression coefficients obtained from **Table 6**. can be rewritten in the form of the following equation.

$$\hat{Y}_t = 1{,}202 - 0{,}77\hat{F}_{t,1} - 0{,}37\hat{F}_{t,2} - 0{,}005\hat{F}_{t,3} + \varepsilon_t$$

Furthermore, the process of nowcasting economic growth is an OLS regression using the DFM-QML method. The regression results can be seen in the following table.

Table 7. OLS Regression Results on DFM-QML Model

Estimator	Partial				Partial	
	Coefficient	t-statistic	p-value	Decision		
Intercept	1.2063	3.478	0.00123	Significant	RSE	2.301
$F_{t,1}$	-0.6607	-3.369	0.00168	Significant	Adj R-squared	0.2013
$F_{t,2}$	-0.2819	-1.419	0.16357	Not Significant	F-Statistic	4613
$F_{t,3}$	-0.1132	-0.488	0.62821	Not Significant	P-value	0.007291
					Decision	Significant

Based on **Table 7**, only the first common factor is significant to economic growth, while the other 2 are insignificant. However, the three common factors will still be used as predictors in nowcasting because they simultaneously affect economic growth significantly, which can be seen from the p-value <0.01. With the regression coefficients obtained from Table 7. can be rewritten in the form of the following equation.

$$\hat{Y}_t = 1{,}206 - 0{,}66\hat{F}_{t,1} - 0{,}28\hat{F}_{t,2} - 0{,}11\hat{F}_{t,3} + \varepsilon_t$$

In addition, it is necessary to perform several assumption tests on the residuals of the formed model. The first assumption that needs to be tested is the normality test, which is done using the Kolmogorov-Smirnov test. The second assumption is non-multicollinearity, which will be tested with the VIF value. The third assumption is the assumption of homoscedasticity, which is tested using the white test. The fourth assumption is the non-autocorrelation assumption, which is tested using the Durbin-Watson test. The results of these tests are as follows.

Table 8. Assumptions Test Results on DFM Model Residuals

MODEL DFM	ASSUMPTION TESTING			
	Normality	Multicollinearity	Heteroscedasticity	Autocorrelation
DFM-TS	Normal	None	None	None
DFM-QML	Normal	None	None	None

The residuals of each model are considered normal if they have a p-value greater than α = 5%. Based on **Table 8**, both DFM models have typically distributed residuals. Meanwhile, the assumption of non-multicollinearity can be met by all models. This is due to the factor estimation of the number of variables that can eliminate multicollinearity. For the assumptions of heteroscedasticity and autocorrelation, the two DFM models indicated that there were no such symptoms; this means that testing the data for heteroscedasticity accepts the null hypothesis so that it can be said that the assumption of homoscedasticity is fulfilled, and it is easier to implement predictive accuracy in policy analysis. In addition, autocorrelation is thought to be caused by each common factor produced following the vector autoregressive (VAR) equation, which is influenced by its past values. It is also suspected to be due to the autocorrelation tendency in the macroeconomic indicators used in this study. Overall, if the regression model meets all these assumptions, it is considered a good and valid model for analysis and prediction. The model provides unbiased, efficient, and consistent estimates.

3.5 Nowcasting Result and Model Goodness Test

In this research, two nowcasting processes were carried out: nowcasting on training and testing data. Nowcasting on testing data will measure the model's goodness by comparing nowcasting results and actual data. Nowcasting in the training data period is used as an additional analysis tool that provides an overview of whether nowcasting is also carried out throughout the training data period. This research uses a visual analysis approach through graphs and quantitative analysis to measure and compare the model's goodness. Graph analysis will look at the comparison of time series plots between nowcasting results and actual data. Quantitative analysis uses measures that describe the amount of error, including Root Mean Square Error (RMSE), Mixed Absolute Percentage Error (MAPE), and Mean Absolute Deviation (MAD).

Comparison of nowcasting results of DFM-TS and DFM-QML models with actual data.

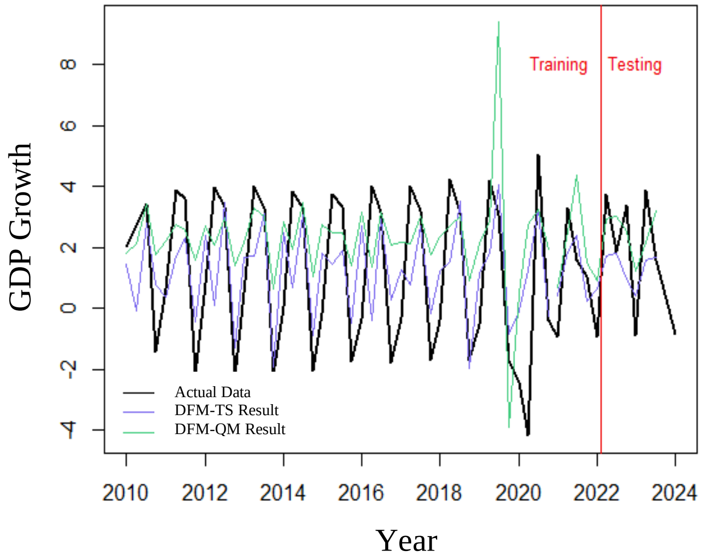

Figure 4. Comparison of Nowcasting Results of DFM-TS and DFM-QML Models with Actual Data.

Based on **Figure 4** during the training period, the prediction results of the DFM-TS model are close to the actual data, indicating that the DFM-TS model can capture the patterns and fluctuations in GDP growth well. The deviation between the actual data and the DFM-TS prediction in this period is minimal, indicating a high fit. However, the DFM-TS model was unable to capture the model in 2020. Although the DFM-TS predictions are still quite good in the testing period, there are some deviations, especially when there are unexpected fluctuations in the actual data. This could indicate that the DFM-TS model may not be able to fully accommodate unexpected events or drastic changes not present in the training data. The DFM-QML model shows a higher deviation in the training and testing periods than the DFM-TS model. In addition, the nowcast results overestimate 2019 to 2020.

Table 9. Measures of Goodness of DFM-TS and DFM-QML Models in Nowcasting

Model	RMSE	MAPE	MAD
TS	1.71035	0.88815	2.075752
QML	1.71598	1.0971	2.09944

The DFM-TS model tends to be superior in prediction accuracy compared to the DFM-QML model. Lower RMSE, MAPE, and MAD values indicate this. The DFM-QML model performs slightly less than the DFM-TS, but the difference is insignificant. However, the higher MAPE value indicates that DFM-QML may have greater difficulty predicting percentage changes.

4. CONCLUSIONS

Based on the results and discussion, it is concluded that the DFM-TS method is better than DFM-QML in GDP nowcasting because it has a greater Adjusted R-squared value and a smaller estimation error rate. In addition, the DFM-TS model can capture patterns and fluctuations in GDP growth better than the DFM-QML model because, in the training and testing periods, the DFM-QML model shows a higher deviation than the DFM-TS model. The nowcasting results overestimate 2019 to 2020.

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