NOWCASTING VIETNAM'S EXPORT GROWTH WITH MIXED FREQUENCY DATA

ABSTRACT

Purpose: The primary objective of this study is to investigate and employ a practical and meaningful nowcasting model to predict Vietnam's export growth based on factors of export supply and demand alongside relevant financial indicators.

Theoretical Framework: This study employs the concepts and theories of nowcasting model with mixed frequency data to create the conceptual framework.

Methodology: This study employs four commonly-used models in nowcasting: the bridge equation model (BEQ), Bayesian VAR model (BVAR), mixed frequency vector autoregressive model (MFVAR), and mixed data sampling regression (MIDAS).

Findings: According to the experimental findings, the mixed frequency data models outperformed the models utilizing the same frequency data in nowcasting Vietnam's export growth. Additionally, this model demonstrated effectiveness in instantaneous and short-term forecasting. MIDAS emerged as the most suitable choice for nowcasting Vietnam's export growth among the models examined.

Implication of Research: using data with mixed frequency along with corresponding methods is the good way for nowcasting.

Originality/Value: This study used macroeconomics factors to nowcast the export growth in Vietnam. It applied four different models including BEQ, BVAR, MFVAR, and MIDAS. The study reveals the roles of data and the potential capability in nowcasting of MIDAS model.

Keywords: Nowcasting, Export Growth, Mixed Frequency Data, Mixed Data Sampling Regression.

NOTIFICANDO O CRESCIMENTO DAS EXPORTAÇÕES DO VIETNÃ COM DADOS DE FREQUÊNCIA MISTA

RESUMO

Objetivo: O objetivo principal deste estudo é investigar e empregar um modelo de previsão prático e significativo para prever o crescimento das exportações do Vietnã com base em fatores de oferta e demanda de exportação juntamente com indicadores financeiros relevantes.

Estrutura Teórica: Este estudo emprega os conceitos e teorias de modelo de nowcasting com dados de frequência mista para criar a estrutura conceitual.

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**Metodologia:** Este estudio emplea cuatro modelos comúnmente usados en nowcasting: el modelo de ecuación de puente (BEQ), el modelo VAR bayesiano (BVAR), el modelo autorregresivo de vector de frecuencia mixta (MFVAR) y la regresión de muestreo de datos mixtos (MIDAS).

**Constataciones:** De acuerdo con las descubiertas experimentales, los modelos de datos de frecuencia mixta superaron a los modelos utilizando los mismos datos de frecuencia en el crecimiento de las exportaciones de Vietnam. Además, este modelo demostró eficacia en previsiones instantáneas y a corto plazo. MIDAS surgió como la opción más adecuada para transmitir el crecimiento de las exportaciones vietnamitas de ahora entre los modelos examinados.

**Implicación de la pesquisa:** usar datos con frecuencia mixta, juntamente con métodos correspondientes, é a boa maneira de se fundir agora.

**Originalidade/valor:** Este estudio utilizó factores macroeconómicos para calcular el crecimiento de las exportaciones de Vietnam. Aplicó cuatro modelos diferentes, incluyendo BEQ, BVAR, MFVAR e MIDAS. El estudio revela los papeles de los datos y la capacidad potencial de la difusión del modelo MIDAS.

**Palavras-chave:** Nowcasting, Crecimiento de Exportaciones, Dados de Frecuencia Mixta, Regresión de Muestreo de Datos Mistos.
1 INTRODUCTION

Export is an important factor affecting each country's economic growth. According to the macroeconomic approach, exports are one of the economy's aggregate demand components. Consequently, when exports increase, aggregate demand rises, promoting the country's economic growth from the aggregate demand side (Mankiw et al., 1995). From an international trade perspective, exports allow countries to specialize in producing goods with a comparative advantage, thereby optimally allocating resources and increasing overall economic productivity (Krugman, 1979). Thence, export forecasting, especially nowcasting, plays a crucial role in shaping business strategies, managing risks, allocating resources and influencing economic and trade policies. International organizations and government agencies, including the International Monetary Fund and the Bank of France, show significant interest in this subject matter. Notably, a study funded by the Bank of France and conducted by Chinn et al., 2023 employed machine learning techniques to nowcast world trade. In general, the nowcasting method of predicting macroeconomic indicators has garnered considerable attention. Jansen et al., 2016 used 12 models to forecast and provide real GDP forecasts for five European countries with quarterly and monthly data. Similarly, Modugno, 2013 introduced a method for nowcasting inflation using data with a higher sampling frequency than monthly. Saha et al., 2022 argued that the nowcasting method can play an important role in providing insights into policymakers' timelines of information released with significant time lags. Therefore, nowcasting a country's export growth is a meaningful research application.

In export forecasting studies, it is common to observe that usage data are published infrequently. These publications tend to vary in terms of frequency and may also be subject to certain delays. Therefore, it is crucial to acknowledge that employing conventional econometric models on data of identical frequencies can lead to an escalation in forecast errors. Understanding this, it becomes imperative to explore alternative approaches to enhance the accuracy of export forecasting.

In recent years, some notable studies have shown the nowcasting method with mixed frequency data improved the accuracy of forecast outcomes, such as Jansen et al., 2016 and Cantú-Bazalduá, 2021. This analytical method has the advantage of optimal exploitation of published data at different frequencies, possibly by day, month, quarter, or year. This type of nowcasting model allows us to forecast economic indicators at a low frequency (such as a quarter) according to the data of exogenous variables collected at a higher frequency (such as days and months). Then, according to the released data stream, by day or month, for example,
one can update the forecast of economic indicators at the quarterly frequency in the current and subsequent quarters. In other words, nowcasting models based on mixed frequency data allow the forecast to be updated according to the real-time data stream; every time the data is published, the forecast results will be adjusted to closely match the evolution of the socioeconomic situation.

Studies on Vietnam's export forecasting have focused on models using data sets of the same frequency and traditional methods like Autoregressive Integrated Moving Average (ARIMA) (Nguyet et al., 2019; Hung and Vi, 2023). Moreover, the nowcast of exports in Vietnam has received limited attention due to the significant lag between preliminary and official export data, which hinders accurate and timely predictions using such traditional methods.

Therefore, in this paper, we focus on building a nowcasting model of export growth in Vietnam using a mixed frequency data set (quarterly, monthly) of economic variables to examine the sample collected from 2009‒2022. In our empirical study in Vietnam, we compare four models – the bridge equation model, the BVAR model, the MFVAR model and the MIDAS model – to nowcast Vietnam's export growth and evaluate the forecasting effectiveness of these models. These models have been employed in various studies to explore the realm of nowcasting other macroeconomic indicators, as evidenced by the works of Kuzin et al., 2011, Modugno, 2013 and Jansen et al., 2016. Our nowcasting model of export growth has the merit of MIDAS and is suitable for forecasting results for many horizons.

2 LITERATURE REVIEW

Macroeconomic forecasts, including exports, have fascinated economists worldwide for years, employing various approaches, from traditional to modern. Some researchers have used autoregressive models incorporating moving averages (ARIMA) to forecast future production and exports based on past trends, such as Başer et al., 2018 in Turkey and Urrutia et al., 2019 in the Philippines. According to Urrutia et al., 2019, when compared with the Bayesian artificial neural network, the export predictor value gave better results than the ARIMA model when there was no significant difference between the actual values and forecast values for both exports and imports of the Philippines. The Bayesian artificial neural network also helped improve Swiss exports' forecast accuracy (Eckert et al., 2012) by allowing for an unambiguous estimation of collation biases, providing coherent forecasts. In addition, when forecasting exports with large and nonlinear data sets, the researchers also used the long short-term memory
Nowcasting Vietnam's Export Growth with Mixed Frequency Data

(LSTM) model, based on artificial neural network theory, and fuzzy system theory to design a model of China's exports (Qu et al., 2019; Bin and Tianli, 2020). The conclusions showed that the machine learning method provides results with smaller errors than the traditional time series regression model.

Nowadays, nowcasting models utilise early available correlated variables to provide 'early estimates' before official data are released (Choi and Varian, 2012; Bańbura et al., 2013). These real-time estimates are valuable for efficient decision-making by organizations, governments, businesses and individuals (Marcellino and Sivec, 2021). This approach has been applied to forecast other macroeconomic indicators, such as GDP, but has not been investigated more deeply in export growth forecasting. Several remarkable studies are as follows.

Nowcasting of Russian exports – when combined with several machine learning models such as Elastic Networks, Random Forests, XGBoost and SSVS on an export-related multivariate dataset – also gave estimates of the highest quality compared to the basic ARIMA model (Майорова and Фокин, 2021). Similarly, the results in the study of Furukawa and Hisano, 2022 indicated that instantaneous forecasting of Japanese exports with the use of machine learning techniques and maritime big data has improved the accuracy and closely followed the movements of exports in a reasonable way when there are fluctuations. Chinn et al., 2023 also used pre-selection, factor extraction and machine learning regression to improve world trade forecasting performance. Notably, Cantú-Bazalduá’s, 2021 research focused on real-time prediction of global trade in goods and services. This study developed a novel approach utilizing dynamic factor models that account for variables with varying frequencies. Despite the scarcity and delayed availability of data, this method exhibits promising prospects for short-term forecasting of exports by leveraging the latest economic data upon its release, even when such data are aggregated infrequently.

In Vietnam, many studies have discussed export forecasting with forecasting total export turnover or a commodity's output and export prices, focusing on traditional methods like ARIMA. Nguyet et al., 2019 and Hung and Vi, 2023 used the ARIMA model to forecast the export value of the last six months of 2018 and Vietnam's export coffee output from 2020 to 2030. For forecasts with seasonal factors, Ngọc et al., 2018 and Diep, 2022 used the Seasonal Autoregressive Integrated Moving Average model (SARIMA) to forecast the export prices of shrimp in 2017 and Vietnam's forecast export value in the period from January 2000 to May 2021, respectively, with data collected from VietstockFinance.

The above export forecasting models were performed with data sets collected in time series with the same frequency in the same period, such as with monthly (Eckert et al., 2012;
Ngoc et al., 2018; Nguyet et al., 2019; Qu et al., 2019; Diep, 2022), quarterly (Urrutia et al., 2019) or annual (Başer et al., 2018; Hung and Vi, 2023) frequency. The processing of data for the same frequency and the same period does not exploit all the variables that could be included in the model and also causes errors, which makes the accuracy of the forecast results low. Moreover, the above studies stop at long-term forecasting without providing short-term forecast results or immediate forecasts, which makes businesses and policymakers encounter difficulties in making production and business decisions corresponding to the actual situation in export activities and quickly detecting changes and trends in export growth to have timely responses.

Given the importance of exports to the development of a highly open economy like Vietnam, a model that uses readily available, timely and multi-frequency information is needed to form 'instantaneous' forecasts for export growth. However, to date, there have not been many studies that have done this. Therefore, this article focuses on the nowcasting of Vietnam's export growth based on mixed frequency data.

3 METHODOLOGY

This study formally presents the export growth nowcasting problem as follows.

Assume \( y_{tq} \) is denoted for export growth, where \( t_q \) is the quarterly time index, \( t_q = 1, 2, 3, ..., T_q^{y} \), with \( T_q^{y} \) as the final quarter in which export growth is available. With \( t_m \) as the monthly time index, export growth is observed in each month’s \( t_m = 3, 6, 9, ..., T_m^{y} \), with \( T_m^{y} = 3T_q^{y} \). Thus, \( y_{t_m+h_m}^{y} \) is denoted for the export growth that will be forecasted \( h_q \) quarters ahead, with \( h_m = 3h_q \).

This study uses four models that have been commonly used in the nowcasting problem: the bridge equation model, Bayesian VAR model (BVAR), mixed frequency vector autoregressive model (MFVAR) and mixed data sampling regression (MIDAS).

3.1 BRIDGE EQUATION MODEL

The bridge model is often applied to short-term forecasts and nowcasts for economic or financial indicators in central banks and policymaking institutions (Baffigi et al., 2004; Diron, 2008; Bencivelli et al., 2012; Jansen et al., 2016). The bridge equation model is an approach that brings many advantages to filtering and combining variables with different frequencies. This technique makes early estimates of low frequency variables based on high frequency
variables. Thus, bridge equations are linear regressions that combine/connect ('bridge') high frequency variables to low frequency variables.

The bridge equation model consists of two steps. Step 1 forecasts the high frequency variables to add the missing data using univariate time series models, and all values of high-frequency variables are then aggregated to obtain their respective low frequency values. The target of this step is to transform high frequency variables into ones with the same frequency as the dependent variable. In Step 2, by using the bridge equation, the regression is performed with the aggregated values to forecast the dependent variable. Therefore, the bridge model can be expressed as the following equation:

\[
y_t = \alpha + \sum_{i=1}^{P} \beta_i(L)x_{i,t} + u_t
\]  \hspace{1cm} (1)

Where:

\(\beta_i(L)\) is a lag polynomial of length \(k\); \(x_{i,t}\) are the selected high frequency indicators aggregated at quarterly frequency; \(p\) is the number of lags in the bridge equation and \(u_t\) is a normally distributed error term.

The selection of high frequency indicators is usually based on a general-to-specific methodology and relies on different in-sample or out-of-sample criteria, such as RMSE performance.

3.2 BAYESIAN VAR MODEL (BVAR)

The Bayesian VAR (BVAR) model is an estimation technique that employs Bayesian methods to estimate a vector autoregression (VAR) model. BVAR with shrinkage techniques has the capability to handle larger unrestricted VAR models. Previous studies by Carriero et al., 2016 and Giannone et al., 2015 have demonstrated the effectiveness of this approach in accommodating and estimating larger VAR models.

The Bayesian VAR model is described as follows:

\[
Z_{t} = \alpha + \sum_{i=1}^{P} A_i Z_{t-i} + u_{t}
\]  \hspace{1cm} (2)

Where:
\[ Z_{t_q} = \left( y_{t_q}, x_{1,t_q}, x_{2,t_q}, \ldots, x_{k,t_q} \right) \], \( u_{t_q} \) is a white noise (WN) process; the coefficients \( A_1, A_2, \ldots, A_p \) are assumed a priori to be independent and normally distributed; and the covariance matrix of the residuals is assumed to be diagonal \( \Sigma = \text{diag}(\sigma_1^2, \sigma_2^2, \ldots, \sigma_k^2) \). The variables are stationary.

3.3 MIXED FREQUENCY VECTOR AUTOREGRESSIVE MODEL (MFVAR)

MFVAR is the model proposed by Mariano and Murasawa, 2003 that allows the analysis of data sets with different frequencies. By using all the high frequency data, compared to the traditional VAR model, this model takes advantage of the available data and provides more complete analysis results for the output variables.

MFVAR is represented as a state space model in which the state transition equations are determined by VAR with a low frequency. More specifically, in this approach, quarterly series are considered as incomplete monthly series. Then, the aggregation equation for the monthly output variable is expressed as follows:

\[ y_{t_q} = y_{t_m} = \frac{1}{3} y_{t_m}^* + \frac{2}{3} y_{t_m-1}^* + y_{t_m-2}^* + \frac{2}{3} y_{t_m-3}^* + \frac{1}{3} y_{t_m-4}^* \]  

(3)

Where:

\( t_m \) is the corresponding months that \( y_{t_m} \) observed, that is \( t_m = 3, 6, 9, \ldots, T_m \), while \( y_{t_m}^* \) corresponds to unobservable monthly values.

This equation comes from the assumption that the series \( Y_{t_m} \) is the average of the series \( y_{t_m} \) with its lagged variables. The detail description of this equation can be found in Mariano and Murasawa, 2003. Moreover, the process VAR(p) for \( x_{t_m} \) and observed \( y_{t_m}^* \) represented by the following equation:

\[ \phi(L_m) \left( y_{t_m}^*, \mu_y^* \right) = u_{t_m} \]  

(4)

Here:

\( x_{t_m} \) and \( y_{t_m}^* \) are variables with high frequency, and \( u_{t_m} \) is a random error with zero expectation and constant variance.
The parameters in the model were interpreted and estimated based on the state space model with maximum likelihood estimation.

3.4 MIDAS MODEL

MIDAS is a regression model proposed by Ghysels et al., 2007 that uses data with mixed frequencies. This model was developed with many variations, such as U-MIDAS, STEP-MIDAS, ADL-MIDAS, EAW-MIDAS and BW-MIDAS. With the advantages of directly processing mixed frequency data and minimising the number of estimated parameters, MIDAS has been widely applied in economic and financial studies. According to results of Kuzin et al., 2011, MIDAS is effective for nowcasting and short-term forecasting.

The MIDAS model directly predicts the value of the output variable in low frequencies based on the high frequency variables, without the need for the same frequency variation as the bridge equation model. In this study, the quarterly export growth – the dependent variable in low frequency – is forecasted through the monthly independent variables in high frequency along with some of the quarterly frequencies.

The basic MIDAS model for forecasting horizon $h$ is described as follows:

$$y_{t_q+h_q} = \beta_0 + \beta_1 B(L_m, \theta)x_{t_m+w}^{(3)} + \epsilon_{t+m+h_m}$$  \hspace{1cm} (5)

Where:

$t_m = 1, 2, \ldots, T_m^x$ is the time index for the monthly sampling frequency of $x$, in which $T_m^x$ is the final month in which an observation is available; $x_{t_m} = x_{t_m}, t_m = \cdots, T_m^x - 6, T_m^x - 3, T_m^x$ means that each third observation, beginning from the $t_0$th observation, is contained in the regressor $x_{t_m}^{(3)}; w = T_m^x - T_m^y$ is the number of monthly periods earlier than the export growth that the monthly indicators $x$ are available; $B(L_m, \theta) = \sum_{k=0}^{K} c(k, \theta) L_m^k$ as a lag polynomial with $c(k, \theta)$ indicates the weight for lag $k$; and $L_m$ is a monthly lag operator so that $L_m x_{t_m} = x_{t_m-1}$. Therefore, the export growth is directly forecasted by $x_{t_m+w}^{(3)}$ and its lags.

Since the indicator $x$ is observed at a higher frequency than $y$, the problem with the MIDAS model is over-parameterisation in adequate modelling with unrestricted cases. To optimise the number of estimated parameters, some weight schemes for lagged polynomials were proposed and discussed by Ghysels et al., 2007. They are the exponential Almon
polynomial, beta polynomial and Step function. In this study, the Almon exponential weight polynomial was used and defined as the following equation:

\[ c(k, \theta) = \frac{\exp(\theta_1 k + \cdots + \theta_Q k^Q)}{\sum_{k=0}^{Q} \exp(\theta_1 k + \cdots + \theta_Q k^Q)} \]  \(6\)

Where:

\( k \) is the delay, \( Q \) is the degree of the polynomial and \( \theta_i (i = 1, \ldots, Q) \) are parameters that need to be estimated. In this study, we selected the Almon polynomial with degree \( Q = 1 \), as in the studies of Ghysels et al., 2007 and Kuzin et al., 2011.

3.5 RESEARCH DATA

The research was carried out on a dataset of macroeconomic indicators collected with different frequencies (quarterly, monthly) from the websites of the General Statistics Office, the International Monetary Fund, the World Bank, the Asian Development Bank, the CEIC database and The Global Economy. The data preprocessing and result representation were performed using Excel, while the analysis and forecasting with models were conducted using Eviews 12.

The study uses a dataset of 18 variables (12 quarterly and 6 monthly frequency variables) to forecast the quarterly export growth rate. Variables representing the supply side include balance of trade (quarterly and monthly), industrial production growth (quarterly and monthly), import growth (quarterly and monthly), GDP growth of Vietnam and retail sales growth. Variables representing the demand side include GDP growth of the United States, GDP growth of Germany and GDP growth of the Netherlands – these are the three countries with the largest import turnover of goods from Vietnam (we collected data on GDP of the top 10 importing countries for products exported by Vietnam, but after a process of choosing a variables set that gives the smallest nowcasting errors, these three countries were selected). The remaining variables represent the price and financial indicators, including money supply growth (quarterly and monthly), interest rate (monthly), interest rate growth (quarterly), monthly exchange rate (average), quarterly exchange rate growth and change of consumer price index.

The variables are described in detail in the following tables (The variable column is the abbreviation for the independent variables used in the model, the economic indicator column is the full name of the variables).
Table 1

Valid variables used in the study

<table>
<thead>
<tr>
<th>Dependent variable: EX_G – Export Growth (%) (monthly)</th>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Independent variables</th>
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<table>
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<tr>
<th>Export demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly</td>
</tr>
<tr>
<td>Economic indicator</td>
</tr>
<tr>
<td>------------------</td>
</tr>
<tr>
<td>GDP growth of the United States (%)</td>
</tr>
<tr>
<td>GDP growth of Germany (%)</td>
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<tr>
<td>GDP growth of the Netherlands (%)</td>
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</tbody>
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<table>
<thead>
<tr>
<th>Export supply</th>
</tr>
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<tbody>
<tr>
<td>Monthly</td>
</tr>
<tr>
<td>Economic indicator</td>
</tr>
<tr>
<td>------------------</td>
</tr>
<tr>
<td>Balance of trade by month (%)</td>
</tr>
<tr>
<td>Industrial production growth by month (%)</td>
</tr>
<tr>
<td>Import growth by month (%)</td>
</tr>
<tr>
<td>GDP growth of Vietnam (%)</td>
</tr>
<tr>
<td>Retail sales growth (%)</td>
</tr>
</tbody>
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<table>
<thead>
<tr>
<th>Price and financial indicators</th>
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</thead>
<tbody>
<tr>
<td>Monthly</td>
</tr>
<tr>
<td>Economic indicator</td>
</tr>
<tr>
<td>------------------</td>
</tr>
<tr>
<td>Money supply growth by month (%)</td>
</tr>
<tr>
<td>Interest rate by month (%)</td>
</tr>
<tr>
<td>Monthly exchange rate growth USD/VND</td>
</tr>
<tr>
<td>Change of Consumer Price Index (%)</td>
</tr>
</tbody>
</table>

Source: Data analysis results of the authors

Based on the methods employed in the study, it is necessary to normalise the data series included in the analysis. This study utilised the Z-score normalisation method. This method involves subtracting the mean value of the data series from the original series and dividing it by the standard deviation. By normalising the data series, they become stationary.

3.6 FORECAST DESIGN

The available data were split into two sets: the training set and the test set. The training set consisted of data from 38 observations spanning the period from 2009.III–2018.IV. The test set, which is used to evaluate the predictive performance of the models, comprises 13 observations covering the period from 2019.I–2022.I.
Nowcasting Vietnam’s Export Growth with Mixed Frequency Data

Table 2

Training set $D = (Y, X)$

<table>
<thead>
<tr>
<th>Training set</th>
<th>Y (Dependent variable)</th>
<th>X (Independent variables)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Three quarters ahead</td>
<td>$Y_{2010.II} \ldots Y_{2010.III} \ldots Y_{2018.IV}$</td>
<td>$X_{2009.III} \ldots X_{2009.IV} \ldots X_{2018.I}$</td>
</tr>
<tr>
<td>Two quarters ahead</td>
<td>$Y_{2010.I} \ldots Y_{2010.II} \ldots Y_{2018.IV}$</td>
<td>$X_{2009.I} \ldots X_{2009.II} \ldots X_{2018.II}$</td>
</tr>
<tr>
<td>One quarter ahead</td>
<td>$Y_{2009.IV} \ldots Y_{2010.I} \ldots Y_{2018.IV}$</td>
<td>$X_{2009.III} \ldots X_{2009.IV} \ldots X_{2018.III}$</td>
</tr>
<tr>
<td>Nowcast</td>
<td>$Y_{2009.III} \ldots Y_{2009.IV} \ldots Y_{2018.IV}$</td>
<td>$X_{2009.IIII} \ldots X_{2009.IV} \ldots X_{2018.IIV}$</td>
</tr>
</tbody>
</table>

Note: X independent variables can be quarterly or monthly frequency.
Source: Data analysis results of the authors

Forecasting refers to forecasts one, two or three quarters ahead, and nowcasting refers to the current quarter forecast, before the official export growth figures become available.

4 RESULTS AND DISCUSSION

4.1 RESULTS

The results of the data analysis give the forecast errors of the models as follows:

Table 3

Forecasting performances of the statistical models (RMSFE), 2019.I–2022.I

<table>
<thead>
<tr>
<th>Model</th>
<th>BEQ</th>
<th>BVAR</th>
<th>MFVAR</th>
<th>MIDAS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Three quarters ahead</td>
<td>3.780</td>
<td>3.960</td>
<td>1.512</td>
<td>2.230</td>
</tr>
<tr>
<td>Two quarters ahead</td>
<td>2.860</td>
<td>1.420</td>
<td>1.275</td>
<td>1.264</td>
</tr>
<tr>
<td>One quarter ahead</td>
<td>2.570</td>
<td>1.722</td>
<td>1.183</td>
<td>0.943</td>
</tr>
<tr>
<td>Nowcast</td>
<td>2.083</td>
<td>1.326</td>
<td>1.044</td>
<td>0.777</td>
</tr>
</tbody>
</table>

Notes: BEQ: bridge equation; BVAR: Bayesian VAR model; MFVAR: mixed frequency vector autoregressive model; MIDAS: mixed data sampling model. Italic entries represent the model with the lowest RMSFE in a column, while bolded entries illustrate the model with the lowest RMSFE in a row (for a particular horizon).
Source: Data analysis results of the authors

Table 3 shows the forecasting performances of four statistical models: BEQ, BVAR, MFVAR and MIDAS. These models were evaluated for the test set, which spans from 2019.I–2022.I, covering a period of 13 quarters. The accuracy of these forecasts was measured using the root mean square forecast error (RMSFE). The empirical analysis was conducted quarterly, considering four different horizons.

The results in Table 3 show several points of interest. First, it can be seen that, when utilising the four training data sets, the nowcast set provides the best prediction results. The forecast error was found to be at its smallest when using the nowcast set, but as we extended
our forecast horizon to one quarter, two quarters and the next three quarters, we observed a gradual increase in the forecast error. It is evident that in the BEQ, BVAR, MFVAR and MIDAS models, the forecast errors for the next three quarters amount to 3.78, 3.96, 1.512 and 2.23, respectively. These figures are approximately two or three times higher than the forecast errors observed with the nowcast training set, which stood at 2.083, 1.326, 1.044 and 0.777, respectively.

Second, the MIDAS and MFVAR models using data with different frequencies (quarterly, monthly) give smaller forecast errors than the BEQ and BVAR models, in which the data refer to the same frequency. Models that fully exploit the available monthly information generally stay competitive up to the two quarters ahead horizon. Among the four models, the MIDAS model gives the best prediction results with the smallest RMSFE in the three training sets with 1.26 at two quarters ahead forecast, 0.94 at one quarter ahead forecast and 0.78 at nowcast. However, the MFVAR and MIDAS models’ prediction errors are not significantly different.

Third, the errors in the MIDAS and MFVAR models are almost smaller than 1.5 in the three forecasting horizons. The three threshold is meant as a rough indication of the economic significance of differences in nowcasting ability. Therefore, we find that forecast models with mixed frequency data outperform nowcasting.

Therefore, the analysis results show two models MIDAS and MFVAR are better than the other models. We evaluated the export forecast of Vietnam based on these two models. Errors were calculated as the absolute difference between the actual and predicted values.
Table 4

Nowcast Vietnam’s export growth by MFVAR and MIDAS

<table>
<thead>
<tr>
<th>e (MFVAR)</th>
<th>e (MIDAS)</th>
<th>EX_G_MFVAR</th>
<th>EX_G_MIDAS</th>
<th>EX_G</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.19</td>
<td>5.68</td>
<td>10.39</td>
<td>10.89</td>
<td>5.21</td>
</tr>
<tr>
<td>0.89</td>
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<td>19.63</td>
<td>14.55</td>
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<tr>
<td>8.92</td>
<td>7.83</td>
<td>MAE (Mean absolute error)</td>
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Notes: Italic entries show small absolute errors while bolded entries illustrate the high absolute errors.
Source: Data analysis results of the authors

The forecast results are obtained based on the standardised data set that has been transformed into the forecast value for Vietnam's export growth. Table 4 shows that the mean absolute error (MAE) of the MIDAS model was lower than the MAE of the MFVAR model by 7.83% and 8.92%, respectively. The absolute forecast error in the short term (from 2019.I–2019.VI) was much smaller than the absolute forecast error at more distant times. Forecasts in the three quarters from 2019.II–2019.IV all had an error of less than 3%. However, in 2019.I, the forecast error had a higher difference than in the remaining three quarters of 2019. In the period 2020.II–2021.I, the forecast error increased sharply compared to 2019; for example, in 2020.II, the errors of the MIDAS and MFVAR models were 16.93% and 24.8%, respectively. There was a significant reduction in the error, although it remained relatively high in the MFVAR model. The errors of this model were consistently above 3%. By contrast, the MIDAS model displayed smaller errors, reaching 0.84% in 2021.II and 0.97% in 2021.IV. However, it is important to note that the MIDAS model also exhibited instances of significantly higher errors, notably peaking at 15.19% in 2021.III.
As shown in Figure 1, the MIDAS model (represented by the green line) provides the closest prediction to the actual data series (represented by the blue line) throughout the entire duration. This model also exhibits a more accurate simulation of the underlying trend than the MFVAR model. However, it is worth noting that there are certain periods – such as 2010, the first half of 2014, and 2018 – during which the MIDAS model deviates from the original model.

During the period from 2019.I–2022.I, both the MIDAS and MFVAR models (represented by the orange line) effectively captured the underlying trend of the original model. It is worth noting that from 2019.I–2021.IV, the MIDAS model demonstrates superior predictive performance compared to the MFVAR model. However, in the remaining period, the MFVAR model proved to be more accurate than the MIDAS model. The outcome of this study aligns quite well with the previous research conducted by Kuzin et al., 2011. Their findings also indicate that the MIDAS model is effective in short-term forecasting and nowcasting, which involves predicting a certain phenomenon's current or near-immediate future values.

4.2 DISCUSSION

In the forecast results, forecast errors in some research periods have variations that may be due to external economic shocks or the distance from the forecast time to the original time.

In 2019, both mixed frequency data models (MIDAS and MFVAR) exhibited relatively small forecast errors, except for a larger forecast error in 2019.I. This anomaly can be attributed
to the influence of the US–China Trade War, which emerged in 2018 and could be a shock to Vietnam's trade activities that was accounted for in the trade demand model used in this study. As Vietnam holds the largest export volume with the US and the largest import volume with China, the repercussions of this trade conflict had a notable effect on Vietnam's export growth during that specific quarter. As a result of seizing the opportunity to replace China in exports to the US, Vietnam's export activities gradually stabilised from the second quarter of 2019 onwards. Therefore, forecast results tend to get better, and forecast errors tend to decrease in the remaining three quarters of 2019, once the shock had been absorbed.

In the period 2020.II–2021.I, it can be seen that the export growth forecast errors in the above two models are much larger than in 2019. This could be explained by the negative impact of the Covid-19 pandemic on the country. Vietnam's economic growth (2020.II GDP growth) is the lowest, by 1.8%, compared to previous quarters. Furthermore, Vietnam's economy faced supply chain disruption and social distancing. This is another shock that was not accounted for in the original trade demand model used in this study.

During the period 2021.II–2022.I, the forecast errors were lower than in the previous period. This can be attributed to Vietnam's successful adaptation to the challenges posed by the Covid-19 pandemic, outperforming many other countries worldwide. Vietnamese businesses have successfully managed to balance the fight against the pandemic while continuing their production and business activities. Notably, domestic export enterprises have taken proactive measures to diversify their sources of raw materials, reducing their reliance on the global supply chain and ensuring stable operations. Consumer demand has also rebounded in key export markets like the US and EU, contributing to an increase in Vietnam's export volume.

The impact of non-economic shocks on the accuracy of both mixed frequency data and nowcasting models suggests that further improvement can be made in the direction of adding data that captures those shocks. This has been shown in research by Barbaglia et al., 2022, which demonstrated the importance of timely information provided by big data to obtain reliable economic predictions, especially the economic context under the impact of the Covid-19 shock. This research also emphasized that models need to be adjusted and changed over time to nowcast economic variables; as well as it is necessary to expand, update and adjust additional information besides big data sources as much as possible.
5 CONCLUSIONS

The process of formulating a comprehensive national export strategy entails numerous factors, and reliable nowcast results for Vietnam's export growth hold important significance within this framework. These forecasts provide valuable insights into market trends, demand patterns and external factors influencing export growth. The primary objective of this study was to utilise the nowcasting method in predicting Vietnam's export growth. This involved considering various factors related to export supply and demand and relevant financial indicators. By incorporating these variables, we aimed to develop a comprehensive and accurate nowcasting model for Vietnam's export growth. In this paper, four models have been used for mixed frequency data analysis: bridge equation (BEQ), Bayesian VAR (BVAR), mixed frequency VAR (MFVAR) and mixed data sampling regression (MIDAS). The paper examined data sets from the period 2009–2022.

The findings indicate that models incorporating mixed frequencies yield lower forecast errors compared to models utilising data of the same frequency. These results align with the research conducted by Marcellino and Sivec, 2021 and Jansen et al., 2016. This suggests that considering variables with different frequencies can improve the accuracy of forecasting models. The results also show that the further past data are from the forecast time, the larger the forecast error Kuzin et al., 2011. This proves that using real-time, continuously updated data combined with a mixed frequency forecast model will improve short-term forecasting efficiency. On the other hand, the volatility trend of the MIDAS model provides the closest prediction to the actual data series, as well as a more accurate simulation of the underlying trend than the MFVAR model. This leads to the suggestion that using the MIDAS model to nowcast Vietnam's export growth during this period has the greatest efficiency among the models. The performance of the MIDAS shows its ability to be used in practice.

In addition, forecasting with real-time data will be the basis of support for relevant state ministries to make appropriate decisions and policies. This is also a suggestion for building recommend systems in the future. However, these systems will face challenges in terms of technical sustainability (Diniz et al -2024) as well as tools in dealing with the problem of information overload Shinde et al (2024).
ACKNOWLEDGMENT

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