PUEY UNGPHAKORN INSTITUTE FOR ECONOMIC RESEARCH

# Analyzing and Forecasting Thai Macroeconomic Data using Mixed-Frequency Approach


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December 2020

Discussion Paper

No. 146

# Final Report on Analyzing and Forecasting Thai Macroeconomic Data using Mixed-Frequency Approach

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December 14, 2020

**Abstract**

Macroeconomic data are an important piece of information in decision making for both the public and private sectors in Thailand. However, the release of key macroeconomic data, usually in a lower frequency such as quarterly, is not always in a timely manner. Using the higher frequency data such as monthly and daily to analyze or forecast the lower frequency data can mitigate the release timing effect. This study applies the mixed-frequency data approach to analyze and forecast Thai key macroeconomic data. The mixed data sampling regressions with various specifications are employed and implemented through some macroeconomic data such as gross domestic product and inflation. The results show that in most cases the mixed-frequency models outperform the autoregressive integrated moving average model, which we used as the benchmark model, even during the COVID-19 period. Some policy implications can also be drawn from the analysis.

*Keywords:* Thai macroeconomic data, mixed-frequency, forecasting, vector autoregression, COVID-19

## 1 Introduction

The release of macroeconomic data has always been a public interest in Thailand. Many organizations, both public and private, and individuals usually base their economic decision on a number of macroeconomic data. Though Thailand is one of the developing economies that have reliable macroeconomic data, the release timing and the forecast accuracy are the important issues that are generally debated and discussed.

The publication lag of some macroeconomic indicators can delay a decision process and produce inaccurate forecasts. This is quite a difficult situation, particularly, for policy and decision makers where the publication delay and less accurate forecasts can easily lead to ineffective measures. Some macroeconomic indicators such as Gross Domestic Product (GDP) are actually available in the higher frequency, e.g., monthly but many researchers and practitioners still rely on the quarterly data with the perception that they are more accurate. Hence, an interesting question arises whether we can make an accurate forecast of the quarterly GDP using other important or related economic indicators that are available in the higher frequency, e.g., monthly.

Previously, the common practice to make a forecast from the data with different frequencies is to aggregate the higher frequent data to have the same frequency as the lower one. However, this does not solve the publication lag issue and can generate the spurious relationship/causality among data, see, among others, Marcellino (1999) and Ghysels, Hill, and Motegi (2016). In addition, this causes the information loss on the dynamic relationship among the data and the opportunity loss to use the timely data releases (Ghysels, 2018). To overcome this, many researchers and practitioners opt to use the recently developed mixed-frequency techniques such as mixed-data sampling (MIDAS) models and state-space models (Foroni and Marcellino, 2013; Ghysels, 2018). In addition to these two models, there are also other techniques that have been used to deal with the mixed-frequency data such as bridge equations and mixed-frequency factor models. There are both pros and cons among these techniques that will be discussed in the literature review section below.

The major advantage of implementing these mixed-frequency techniques on Thai macroeconomic data is to render us with more accurate and timely forecasts. Hence, some modern forecasting techniques such as nowcasting, which is a special case of mixed-frequency forecasting, where the current period is being forecasted become practically possible. In addition, the near-future forecasts can also be more reliable. With more accurate forecasts, policy and decision makers can possibly design the effective policy and measures.

This study aims to explore and find the well-fitted mixed-frequency techniques to some important Thai macroeconomic data such as GDP, inflation, and number of workers. We also expect this study to shed some light on the forecasts of other important data in economics and other areas such as finance and energy. Another desirable outcome would be the widespread use of modern forecasting techniques in Thailand.

In this study, we assess the mixed-frequency models by comparing the generated out-of-sample forecasts through some measures with those of the autoregressive integrated moving average (ARIMA) model, which we used as the benchmark model. We also evaluate how well the models perform when the data during the coronavirus (COVID-19) pandemic are both included and excluded. The results tend to favor the mixed-frequency models. Some policy implications can also be drawn from the results.

The organization of this report is as follows. Section 2 reviews the relevant literature. Section 3 explains the methodology that mainly includes the data and models. Section 4 shows the results. Section 5 concludes.

# 2 Related Literature

## 2.1 Mixed-Frequency Approach and Macroeconomic Data Analysis

The mixed-frequency approach becomes better known for its ability to forecast the data with different sampling frequencies. The growing literature on mixed-frequency techniques reflects the increasing popularity of this approach. Foroni and Marcellino (2013) and Ghysels (2018) provide a comprehensive review of various mixed-frequency techniques. In this section, we focus on the related literature with relevant models and methods.

Temporal aggregation of the higher-frequency data to the lowest ones is an early common approach in dealing with mixed-frequency data. See Wolhrabe (2009) for more details on the review of early mixed-frequency models that use the aggregation and interpolation of data, and the bridge and linkage models. Due to the loss of some useful information and the model misspecification, many researchers tend to model the mixed-frequency data directly.

Direct modeling of mixed-frequency data through bridge equations is a popular technique for forecasting during the early days. Baffigi, Golinelli, Parigi (2004) and Diron (2008), among others, use the bridge equations to link the high-frequency data to the lower ones. Precisely, the bridge equations or regression models with the lower-frequency dependent variable and the higher-frequency independent variables (or indicators) are estimated in two steps to obtain the forecasts for the lower-frequency variable. Basically, the higher-frequency variables are first forecasted, then the forecasts are aggregated and used as the regressors to forecast the lower-frequency data. The regression models used need not be a structural macroeconomic model. Note that in many cases the non-structural macroeconomic models can return a better forecast, see Giacomini (2015) for the relevant discussion. However, the bridge equations do possess sufficient statistical properties. This is probably a reason why Bencivelli, Marcellino, and Moretti (2012) that use the Bayesian Model Averaging can perform empirically well.

MIDAS is one of the recent approaches that are commonly used to tackle the data series with different sampling frequencies. Different from bridge equations, MIDAS uses only one step to estimate a univariate high-frequency regression, see more details in Ghysels, Santa-Clara, and Valkanov (2004, 2005, and 2006), Ghysels, Sinko, and Valkanov (2007), and Schumacher (2016). MIDAS is also called an observation-driven model with tight parameterization. With its reduced form, MIDAS can be implemented without the full specification as in a state-space model (Ghysels, Kvedaras, and Zemlys, 2016). The highly parsimonious distributed lag polynomials of the higher-frequency independent variables help to avoid the parameter proliferation with the lag-order selection problems. Due to its gain in popularity, MIDAS has a number of extensions and variations, see Foroni and Marcellino (2013) for more details.

Another popular model that is used to analyze and forecast the mixed-frequency data is the state-space model, see Ghysels (2018) for an exhaustive list of papers under this category. Due to its settings, this type of model is also called a parameter-driven model where its main tool is the Kalman filter. Bai, Ghysels, and Wright (2013) reveal that the Kalman filter can be exactly represented by some MIDAS regression models. A major advantage of the state-space models is the ability to analyze and forecast the dynamic relationship of multiple variables through multivariate analysis. In addition, the Kalman filter can be used to both make the forecasts and estimate the missing values (Mariano and Murasawa, 2003 and 2010). However, Ghysels, Kvedaras, and Zemlys (2016) indicate that the Kalman filter is sensitive to specification errors and needs many parameters that make it a computationally expensive approach.

In this study, we focus on the MIDAS regressions as they are the commonly used model with the observation-driven approach where the estimation is not computationally demanding and is easy to implement, unlike the parameter-driven approach as in the state-space model. Where applicable and appropriate, we also extend the other models to search for the best-fitted model, in terms of the forecast accuracy, with the mixed-frequency Thai macroeconomic data. For example, Ghysels (2016) illustrates how the vector autoregressive (VAR) models and their structural counterparts are used to analyze the mixed-frequency data. However, the VAR might be suitable for the time frequencies with fixed intervals such as quarterly and monthly.

## 2.2 Central Banks and Nowcasting

Nowcasting can be considered a special case of mixed-frequency forecasting. Nowcasting usually makes the forecasts from the current time period, e.g., quarter whereas some mixed-frequency forecasting methods such as MIDAS with leads can produce the forecasts in any future time periods (Andreou *et al.* 2011, 235-236). See also Banbura *et al.* (2013) for an extensive review on nowcasting. Several central banks have used the mixed-frequency models to nowcast some macroeconomic series. Alessi *et al.* (2014) show that using mixed-frequency models that incorporate financial information can help improve the forecasts made by the European Central Bank and the Federal Reserve Bank of New York during the global financial crisis.

Several central banks have used the dynamic factor models together with the big data techniques to nowcast the quarterly GDP growth through the news impact (Bok *et al.* 2017). The advantage of this approach is the combination of the traditional method that uses many data releases with the judgmental process and the timely assessment of the economic conditions from the news. Thorsrud (2016)suggested if the Norges Bank (the central bank of Norway) used this approach,the forecasting errors would be lower.

Staff members from the Reserve Bank of New Zealand show that using machine learningalgorithms such as support vector machines, least absolute shrinkage and selection operator (or LASSO), and neural networks, can improve the nowcasts of quarterly GDP growth (Richardson, Mulder, and Vehbi 2018). They found the proposed algorithms outperform the usual autoregressive models while the nowcast combination from the machine learning algorithms returns lower errors than those of the factor model and small Bayesian VAR model. Technical reports on nowcasting and mixed-frequency models from many central banks and organizations indicate the promising use of these models and methods in the future, see Liebermann (2011), Dahlhaus, Guénette, and Vasishtha (2015), Buono *et al.* (2018), and Gil *et al.* (2018), among others.

Since the nowcasting is a special case of MIDAS, our assessment of out-of-sample forecasts can implicitly show how the nowcasting can be performed. Our results show that the MIDAS with various specifications performs reasonably well.

# 3 Data and Methodology

## 3.1 Data

The dataset we used in the analysis contains some key macroeconomic and financial variables including quarterly chain-volume gross domestic product (GDP) at 2002 price from the Office of the National Economic and Social Development Council (NESDC) of Thailand, quarterly number of workers in the labor force (LF) from the National Statistical Office (NSO) of Thailand, monthly inflation rate and daily stock price index from CEIC, daily interest rate and exchange rate from the Bank of Thailand (BOT). All these variables are converted to the percentage change with the quarter-on-quarter change for the GDP and LF, the year-on-year change for the inflation, and the previous-day change for the stock index, interest rate, and the exchange rate. Note that, with the change, the stock index becomes the stock return. See more details on the data description in Table 1.

Table 1: Data Description

| Variable | Description | Frequency | Period | Source |
|---|---|---|---|---|
| Real GDP | Chain-Volume Gross Domestic Product (2002 reference year) | Quarterly | Q1, 1993-Q2, 2020 | NESDC |
| No. of Workers | Number of Workers in Labor Force | Quarterly | Q1, 1998-Q2, 2020 | NSO |
| Inflation | Year-on-Year Change of Consumer Price Index (2010 = 100) | Monthly | Jan. 1966-Jun. 2020 | CEIC |
| SET Index | Stock Exchange of Thailand Price Index | Daily | Jan. 1988-Sep. 2020 | CEIC |
| Interest Rate | Weighted Average Overnight Interbank Rates | Daily | Jan. 2011-Sep. 2020 | BOT |
| Exchange Rate | Weighted Average Foreign Exchange Rates | Daily | Jan. 1991-Sep. 2020 | BOT |

Our main purpose is to analyze and forecast the lower frequency variables (GDP, LF, and inflation) using higher frequency variables. That means we use monthly inflation and daily stock return, interest rate, and exchange rate each as a predictor to forecast the quarterly GDP and LF. Similarly, we use the daily data to forecast the monthly inflation. To make a fair comparison, we adjusted the starting period of both lower and higher frequency variables accordingly, especially for the interest rate that has a shorter time span.

## 3.2 Models and Methods

The starting model we used in the analysis is the autoregressive distributed lag mixed data sampling (ADL-MIDAS) that regresses the lower-frequency dependent variable on the higher-frequency explanatory variable(s) or predictor(s). Let $t_L = 1, ..., T_L$ denote the index of lower-frequency data, e.g., quarters, and $m$ is the number of times the higher-frequency data appears in each lower-frequency time unit. That is, $m = 3$ for the case of quarterly data and the monthly indicators as explanatory variables. We denote the lower-frequency variable by $y_{t_L}$ and the higher-frequency variables by $x_{t_H-j/m}$ where $t_H = 1, ..., T_H$ is the time index of higher-frequency data, $t_H - j/m$ is the $j$th (past) high-frequency period with $j = 0, ..., m-1$. That means, for a quarter/month mixture we have $x_{t_H}, x_{t_H-1/3}, x_{t_H-2/3}$ as the last, second to last, and first months of quarter $t_L$. Through some aggregation scheme, such as flow or stock sampling, we can construct a lower-frequency series $x_{t_L}$ where we assume $x_{t_L} = \sum_{i=0}^{m-1} x_{t_H-i/m}$.

According to Andreou, Ghysels, and Kourtelloset (2013), the ADL-MIDAS is given by

$$y^L_{t_L+h} = a_h + \lambda_h y^L_{t_L} + b_h C(L^{1/m}; \theta_h) x^H_{t_L} + \epsilon^L_{t_L+h},$$

where $y^L_{t_L+h}$ is the $h$-step-ahead lower-frequency variable, $a_h$ and $b_h$ are the regression coefficients, $\lambda_h$ is the autoregressive coefficients, $x^H_{t_L}$ is the higher-frequency variable, $C(L^{1/m}; \theta)$ is the parsimonious polynomial specification, $L$ is a lag operator, and $\epsilon^L_{t_L+h}$ is the $h$-step-ahead lower-frequency error term.

A number of parsimonious polynomial specifications $C(L^{1/m}; \theta)$ has been used in the analysis including (1) normalized beta density with a zero last lag, (2) normalized beta density with a non-zero last lag, (3) normalized exponential Almon lag polynomial, (4) unrestricted coefficients, (5) polynomial with step functions, and (6) Almon lag polynomial of order $p$. See Ghysels, Sinko, and Valkanov (2006) for more details on the specifications.

In the estimation, either the non-linear least squares (NLS) or the estimation via profiling can be used to estimate the MIDAS regression models. See Ghysels, Santa-Clara, and Valkanov (2004) and Andreou, Ghysels, and Kourtellos (2010) for more details on the NLS and Ghysels and Qiang (2016) on the profiling.

In addition to the ADL-MIDAS, we also perform the mixed-frequency forecasting through the vector autoregressive model (VAR). The benefits of VAR in the mixed-frequency analysis are to stack the high and low frequency data together with the same time interval, e.g. quarter, and to allow them to be related through the error covariance matrix. The major limitation of the VAR is the data need to have the fixed time intervals, e.g., quarterly and monthly while those of daily data are varied from month to month. Based on Ghysels (2016), the mixed-frequency VAR is given by

$$\mathbf{z}_t = \mathbf{c} + \sum_{j=0}^{P} \mathbf{A}_j \mathbf{z}_{t-j} + \boldsymbol{\epsilon}_t,$$

where $\mathbf{z}_t = (x_{t,1}, \cdots, x_{t,m}, y_t)'$ is the vector of mixed-frequency variables with $m$ higher frequency variables, $\mathbf{c}$ is the vector of constants, $\mathbf{A}_j$ is the matrix of autoregressive coefficients with $P$ lag orders, $\mathbf{z}_{t-j}$ is the corresponding lagged vector of $\mathbf{z}_t$, and $\boldsymbol{\epsilon_t} \sim \boldsymbol{MVN_{m+1}(0, \Sigma)}$ is the error vector that follows the multivariate normal with mean vector $\mathbf{0}$, and $(m+1) \times (m+1)$ covariance matrix $\mathbf{\Sigma}$.

With the limitation on the time intervals, we apply the VAR to analyze and forecast each quarterly lower frequency variable, GDP and LF, using the monthly higher frequency variable, inflation. Hence, in our analysis, $m = 3$ and with the quarterly data we set $P = 4$ or VAR(4). It is not difficult to derive the $h$-step-ahead forecast equation from the above VAR model.

## 3.3 Forecast Accuracy Evaluation

For the sake of comparison, we estimate and forecast the lower frequency variables using the ARIMA model and label it as the benchmark model. To assess and find the best fitted and forecasting model, we employ the commonly-used forecast error measures including root mean squared error (RMSE) and mean absolute percentage error (MAPE). We also use the Diebold-Mariano (DM) test to evaluate the forecast accuracy (Diebold and Mariano, 1995). However, the DM test suffers from two flaws. First, based on the null hypothesis, the DM test mainly assesses if the two forecasts are close. Second, the DM test is likely to reject the null hypothesis, e.g., returning the smaller p-values, for the forecast samples as in our case. Hence, we use the DM test to assess whether the forecasts are different from the true values. The resulting p-value then signifies how well the forecasting model performs, i.e., the higher the p-value, the better the forecasting model is. Again, the DM test results may not be reliable in the small samples.

In the evaluation, we split the data into the training and test sets where the latter is assessed against the out-of-sample forecasts. Since we focus on the short-term forecasting models, all generated forecasts are the 1-step ahead and the forecast horizon is only one year to complete the seasonal patterns. Precisely, for quarterly data, four forecast values are produced while it is twelve data points for the monthly data. We also assess the forecasting performance of the models under the COVID-19 situation and separate the data accordingly. Without the COVID-19, the training set ends December 2018 and the test set is the 2019 data. With the COVID-19 and the data availability, the training set ends at the first half of 2019 and the rest (the second half of 2019 and the first half of 2020) is the test set.

# 4 Results

In this section, we show the forecasting results of three lower frequency variables (GDP, LF, and inflation) across three models (ADL-MIDAS, VAR, and ARIMA). For the ADL-MIDAS, there are six parsimonious polynomial specifications including (1) normalized beta density with a zero last lag (BT), (2) normalized beta density with a non-zero last lag (BNN), (3) normalized exponential Almon lag polynomial (EAM), (4) unrestricted coefficients (UM), (5) polynomial with step functions (ST), and (6) Almon lag polynomial of order $p$ (AM). In the estimation and forecasting, we use the MATLAB software for ADL-MIDAS (see Qian, 2020 for more details) and VAR while R is used for the ARIMA. Hence, the best fitted ARIMA model for each variable is found using the `auto.arima` function in R.

For each lower frequency variable, we assess the models to find the best higher frequency predictor, and the polynomial specification in the case of ADL-MIDAS , in terms of forecast accuracy. That means we obtain the resulting forecasts from different higher frequency predictors (and polynomial specifications) and evaluate them through some forecast error measures. Precisely, we first find the best forecasting model among the mixed-frequency approach, i.e., the ADL-MIDAS with six specifications and the VAR (for quarterly lower frequency dependent variable and monthly higher frequency predictor) across predictors. Then, we compare the best mixed-frequency model with the benchmark model (ARIMA).

For the in-sample fit, we use the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) to assess how well the models perform in the training set. However, due to the different (shorter) length of the data, the AIC and BIC cannot be used for the interest rate to compare with other predictors. Note also that the AIC and BIC may not be the ideal model selection criteria to compare the VAR, which is a multivariate model, with the univariate ADL-MIDAS and ARIMA models because the VAR is heavily penalized from its larger number of parameters. However, we still report the AIC and BIC for completeness.

## 4.1 Gross Domestic Product (GDP)

In the ADL-MIDAS models for the quarterly real GDP growth, we set the lag orders of the dependent variable (quarterly real GDP growth) and the predictor (monthly inflation, daily stock return, daily change in interest rate, and daily change in foreign exchange) to reflect their seasonality, i.e., 4 for quarterly, 12 for monthly, and 5 for daily. The start dates in the estimation are then re-adjusted accordingly.

Without the COVID-19 data in the out-of-sample period, in terms of MAPE and

RMSE, the MIDAS with Almon lag polynomial (AM) is the best performing model when the monthly inflation is used as the predictor (Table 2). The MIDAS with step functions (ST) seems to be the best for daily return and change in foreign exchange rate (Tables 3 and 5) while the MIDAS with normalized exponential Almon polynomial (EAM) is the best for daily change in interest rate (Table 4). Note that the p-value from the DM test (DM-p) does not convey useful information and judgment as its best result returns the model with the high forecast error measures. In terms of AIC and BIC, though some models perform well in the in-sample fit, most of them did not return the best forecasting results.

Table 2: Forecast Error Measures and Model Selection Criteria: Real GDP Growth with Inflation (No COVID)

| | MIDAS | | | | | | VAR(4) |
|---|---|---|---|---|---|---|---|
| | BT | BNN | EAM | UM | ST | AM | |
| MAPE | 26.61 | 26.23 | 25.72 | 26.14 | 21.21 | **21.08** | 26.89 |
| RMSE | 1.12 | 1.08 | 1.11 | 1.11 | **0.89** | **0.89** | 1.37 |
| DM-p | 0.92 | 0.85 | **0.97** | 0.57 | 0.91 | 0.93 | 0.13 |
| AIC | 182.79 | 185.10 | 182.68 | 187.33 | 182.01 | **181.82** | 914.73 |
| BIC | 203.55 | 208.45 | **203.44** | 231.44 | 205.36 | 205.17 | 1,088.39 |

Table 3: Forecast Error Measures and Model Selection Criteria: Real GDP Growth with Stock Return (No COVID)

| | BT | BNN | EAM | UM | ST | AM |
|---|---|---|---|---|---|---|
| MAPE | 17.68 | 13.13 | 12.93 | 21.11 | **11.40** | 20.25 |
| RMSE | 0.78 | 0.53 | **0.50** | 0.89 | 0.51 | 0.84 |
| DM-p | **0.97** | 0.55 | 0.68 | 0.38 | 0.89 | 0.41 |
| AIC | 186.25 | 181.64 | 180.01 | 178.75 | 183.65 | **176.94** |
| BIC | 207.01 | 205.00 | 200.77 | 204.71 | 201.82 | **200.30** |

Table 4: Forecast Error Measures and Model Selection Criteria: Real GDP Growth with Change in Interest Rate (No COVID)

| | BT | BNN | EAM | UM | ST | AM |
|---|---|---|---|---|---|---|
| MAPE | 26.77 | 39.86 | **26.65** | 53.61 | 26.88 | 36.93 |
| RMSE | 1.20 | 1.63 | **1.20** | 1.98 | 1.22 | 1.60 |
| DM-p | 0.72 | **0.84** | 0.75 | 0.83 | 0.76 | 0.78 |
| AIC | 55.91 | 57.91 | 55.93 | 59.37 | **53.93** | 57.56 |
| BIC | 67.38 | 70.82 | 67.40 | 73.71 | **63.97** | 70.46 |

Table 5: Forecast Error Measures and Model Selection Criteria: Real GDP Growth with Change in Foreign Exchange Rate (No COVID)

| | BT | BNN | EAM | UM | ST | AM |
|---|---|---|---|---|---|---|
| MAPE | 28.87 | 20.77 | 37.22 | 43.70 | **19.39** | 43.38 |
| RMSE | 1.16 | 0.86 | 1.54 | 1.77 | **0.80** | 1.85 |
| DM-p | 0.78 | 0.90 | 0.89 | **0.99** | **0.99** | 0.98 |
| AIC | 181.21 | 183.74 | 179.58 | 179.81 | 184.93 | **178.72** |
| BIC | 201.97 | 207.09 | **200.34** | 205.76 | 203.09 | 202.08 |

Across the predictors, the daily stock return seems to be the best predictor as most of its MIDAS specifications return the lower MAPE and RMSE. According to Table 6, the MIDAS with step function (ST) from stock return performs better than the benchmark ARIMA$(0,0,0)(0,1,2)_4$ both in terms of MAPE and RMSE (in bold fonts). This can also be seen in Figures 1 and 2. Actually, half of the MIDAS models from the daily return give lower MAPE values than those of the ARIMA model for the out-of-sample period without the COVID-19 data.

This indicates that under normal circumstances, e.g., without extreme shock, the daily stock return can help predict the quarterly real GDP growth through the MIDAS forecasting model. Intuitively, the daily stock return can reflect the recent economic condition in a timely manner. That shows how people's consumption behavior reacts to the economic condition and that might later affect the GDP.

Table 6: Comparison of Selected Results for Real GDP Growth (No COVID)

| | MIDAS-AM | MIDAS-ST | MIDAS-EAM | MIDAS-ST | ARIMA |
|---|---|---|---|---|---|
| | Inflation | Return | Interest | Forex | $(0,0,0)(0,1,2)_4$ |
| MAPE | 21.08 | **11.40** | 26.65 | 19.39 | 14.60 |
| RMSE | 0.89 | **0.51** | 1.20 | 0.80 | 0.58 |
| DM-p | 0.93 | 0.89 | 0.75 | **0.99** | 0.62 |
| AIC | **181.82** | 183.65 | n.a. | 184.93 | 457.36 |
| BIC | 205.17 | **201.82** | n.a. | 203.09 | 464.89 |

Notes: ARIMA$(p,d,q)(P,D,Q)_m$ refers to $p$ lag orders of AR part, $d$ degrees of first differencing, $q$ lag orders of MA part, $P$ lag orders of seasonal AR part, $D$ degrees of seasonal first differencing, $Q$ lag orders of seasonal MA part, and $m$ seasonal periods, and n.a. = not available.

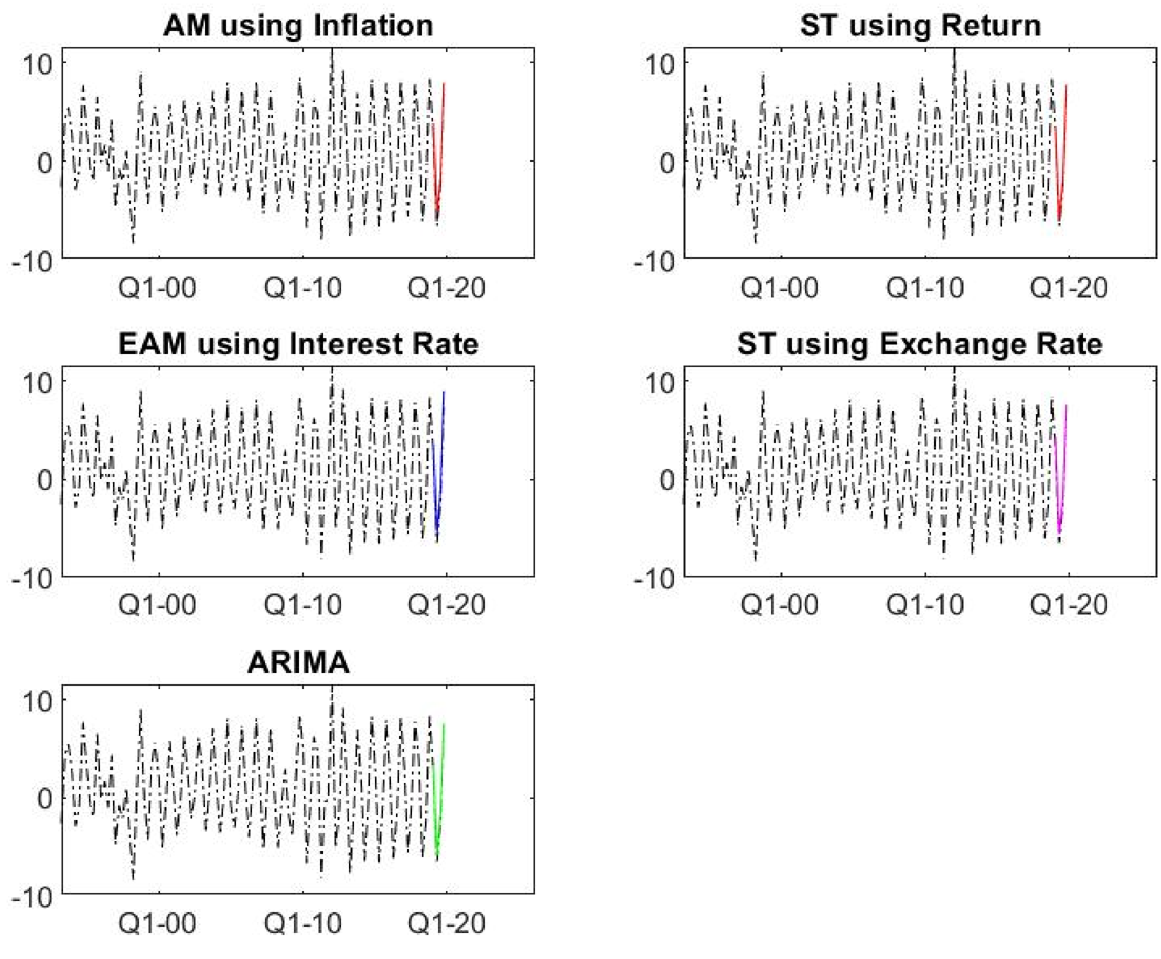


Figure 1: Real GDP Growth and Out-of-Sample Forecasts (in colors) from Various Models during Q1, 1993-Q4, 2019 (No COVID)

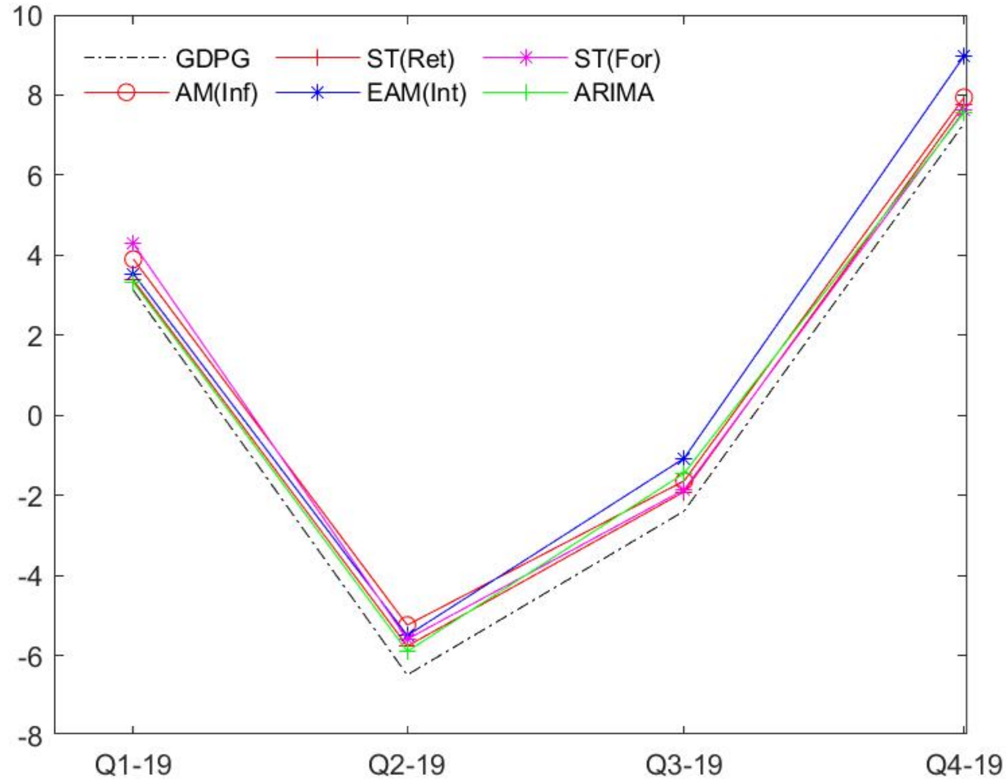


Figure 2: Real GDP Growth and Out-of-Sample Forecasts (in colors) from Various Models during Q1, 2019-Q4, 2019 (No COVID)

The results in Tables 7-10 show that inflation is the best predictor for the real GDP growth when the COVID data are included. It returns the lowest MAPE and RMSE for the unrestricted MIDAS (UM) and the VAR, respectively. Though the daily change in stock return does not yield the lowest forecast errors across the predictors, many of its MIDAS models does return the lower MAPE. The daily change in foreign exchange rate is the worst forecasting model in terms of MAPE so we exclude it in the comparison with the ARIMA model. Again, the p-value from the DM test does not provide any useful information for the comparison.

Table 7: Forecast Error Measures and Model Selection Criteria: Real GDP Growth with Inflation (COVID)

| | MIDAS | | | | | | VAR(4) |
|---|---|---|---|---|---|---|---|
| | BT | BNN | EAM | UM | ST | AM | |
| MAPE | 299.84 | 286.40 | 302.04 | **194.77** | 280.07 | 277.83 | 207.82 |
| RMSE | 6.86 | 6.84 | 6.84 | 7.30 | 6.69 | 6.70 | **2.87** |
| DM-p | 0.50 | 0.50 | 0.50 | 0.50 | 0.49 | 0.49 | **0.85** |
| AIC | 187.71 | 189.73 | 187.71 | 190.22 | 186.43 | **186.15** | 928.04 |
| BIC | 208.64 | 213.26 | **208.63** | 234.68 | 209.97 | 209.68 | 1,103.12 |

Table 8: Forecast Error Measures and Model Selection Criteria: Real GDP Growth with Stock Return (COVID)

| | BT | BNN | EAM | UM | ST | AM |
|---|---|---|---|---|---|---|
| MAPE | 259.73 | 242.16 | 245.93 | 241.48 | 255.31 | **240.81** |
| RMSE | **6.88** | 7.25 | 7.56 | 7.25 | 7.01 | 7.23 |
| DM-p | 0.48 | **0.49** | 0.48 | **0.49** | 0.48 | **0.49** |
| AIC | 190.25 | 185.27 | 183.67 | 182.43 | 187.52 | **180.60** |
| BIC | 211.17 | 208.80 | 204.59 | 208.58 | 205.83 | **204.14** |

Table 9: Forecast Error Measures and Model Selection Criteria: Real GDP Growth with Change in Interest Rate (COVID)

| | BT | BNN | EAM | UM | ST | AM |
|---|---|---|---|---|---|---|
| MAPE | 278.37 | 274.31 | 290.36 | **243.73** | 290.23 | 261.73 |
| RMSE | 7.70 | 7.37 | 7.75 | 7.16 | 7.31 | **6.98** |
| DM-p | 0.49 | 0.47 | 0.48 | 0.46 | **0.50** | 0.47 |
| AIC | 60.83 | 62.11 | 60.83 | 63.48 | **59.81** | 62.67 |
| BIC | 72.80 | 75.58 | 72.80 | 78.45 | **70.28** | 76.14 |

Table 10: Forecast Error Measures and Model Selection Criteria: Real GDP Growth with Change in Foreign Exchange Rate (COVID)

| | BT | BNN | EAM | UM | ST | AM |
|---|---|---|---|---|---|---|
| MAPE | 286.76 | 270.12 | 290.01 | 291.48 | **268.77** | 290.87 |
| RMSE | 6.40 | 6.59 | 6.63 | **5.94** | 6.59 | 6.21 |
| DM-p | 0.50 | 0.49 | 0.49 | 0.50 | 0.48 | **0.50** |
| AIC | 185.84 | 193.08 | 184.25 | 184.51 | 189.10 | **183.45** |
| BIC | 206.77 | 216.62 | **205.18** | 210.66 | 207.40 | 206.99 |

When comparing with the ARIMA model, some mixed-frequency models still perform better than the ARIMA (Table 11 and Figures 3-4). The unrestricted MIDAS and the VAR both using the inflation as the predictor return the lowest MAPE and RMSE, respectively. With the COVID data, the quarterly real GDP growth seems to respond to the monthly inflation than the other variables. This confirms that the severe demand-pull effect during the COVID-19 pandemic does not only drag down the price but also bring down the real GDP growth.

Note that the VAR is actually the better forecasting model than the ARIMA as it returns the lower forecast errors. This is possibly due to the direct correlation with the monthly data that the model explicitly incorporates. Hence, it might be worth attempting to forecast the quarterly real GDP growth using the daily variables through the VAR model. However, this requires more technical efforts and we leave it for future research.

Based on the results from the mixed-frequency forecasting of real GDP growth, we can conclude that the higher frequency variables can help return the better forecasts in this case. In addition, the mixed-frequency approach renders us with some economic insight and implication.

Table 11: Comparison of Selected Results for Real GDP Growth (COVID)

| | MIDAS-UM | MIDAS-AM | MIDAS-UM | VAR(4) | ARIMA |
|---|---|---|---|---|---|
| | Inflation | Return | Interest | Inflation | $(0,0,0)(0,1,2)_4$ |
| MAPE | **194.77** | 240.81 | 243.73 | 207.82 | 238.02 |
| RMSE | 7.30 | 7.23 | 7.16 | **2.87** | 5.97 |
| DM-p | 0.50 | 0.49 | 0.46 | **0.85** | 0.41 |
| AIC | 190.22 | **180.60** | n.a. | 928.04 | 464.45 |
| BIC | 234.68 | **204.14** | n.a. | 1,103.12 | 472.05 |

Notes: ARIMA$(p,d,q)(P,D,Q)_m$ refers to $p$ lag orders of AR part, $d$ degrees of first differencing, $q$ lag orders of MA part, $P$ lag orders of seasonal AR part, $D$ degrees of seasonal first differencing, $Q$ lag orders of seasonal MA part, and $m$ seasonal periods, and n.a. = not available.

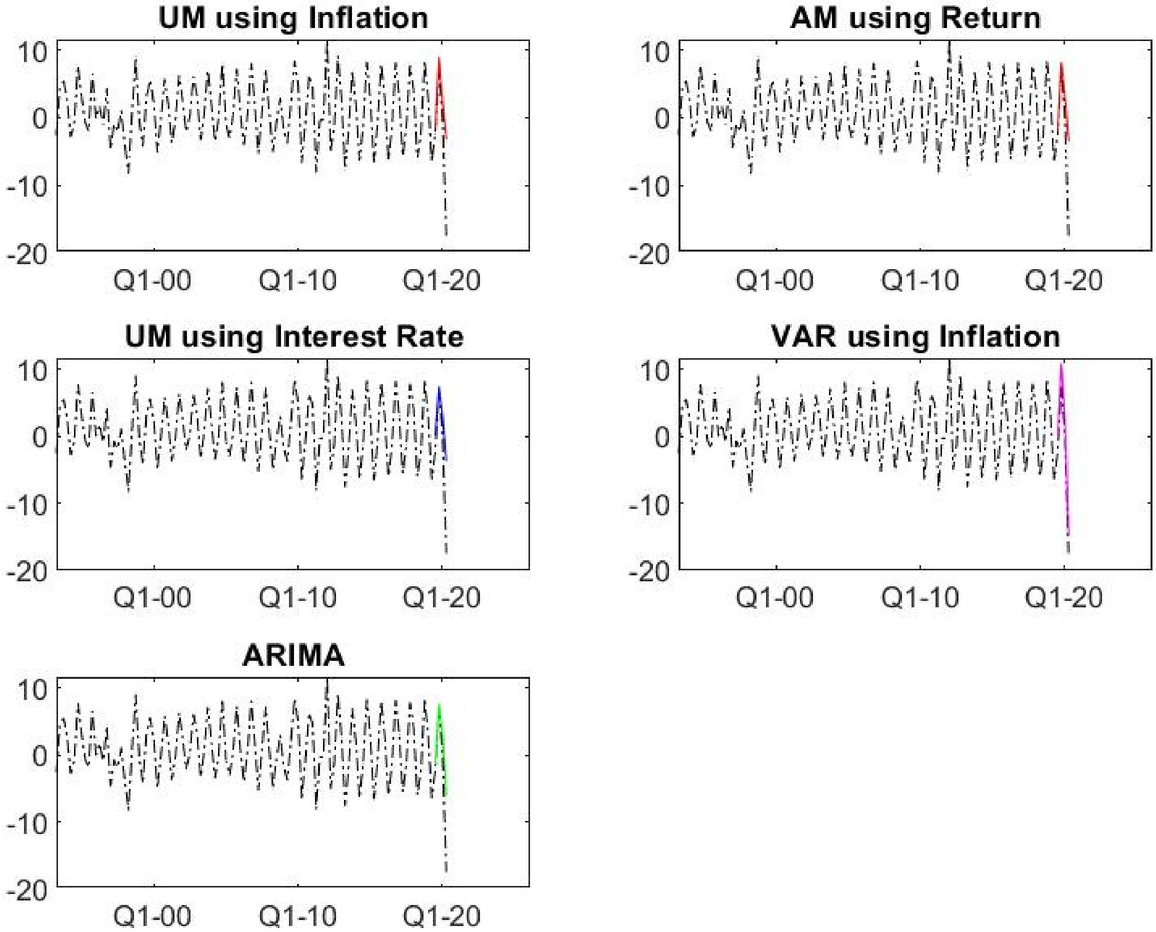


Figure 3: Real GDP Growth and Out-of-Sample Forecasts (in colors) from Various Models during Q1, 1993-Q2, 2020 (COVID)

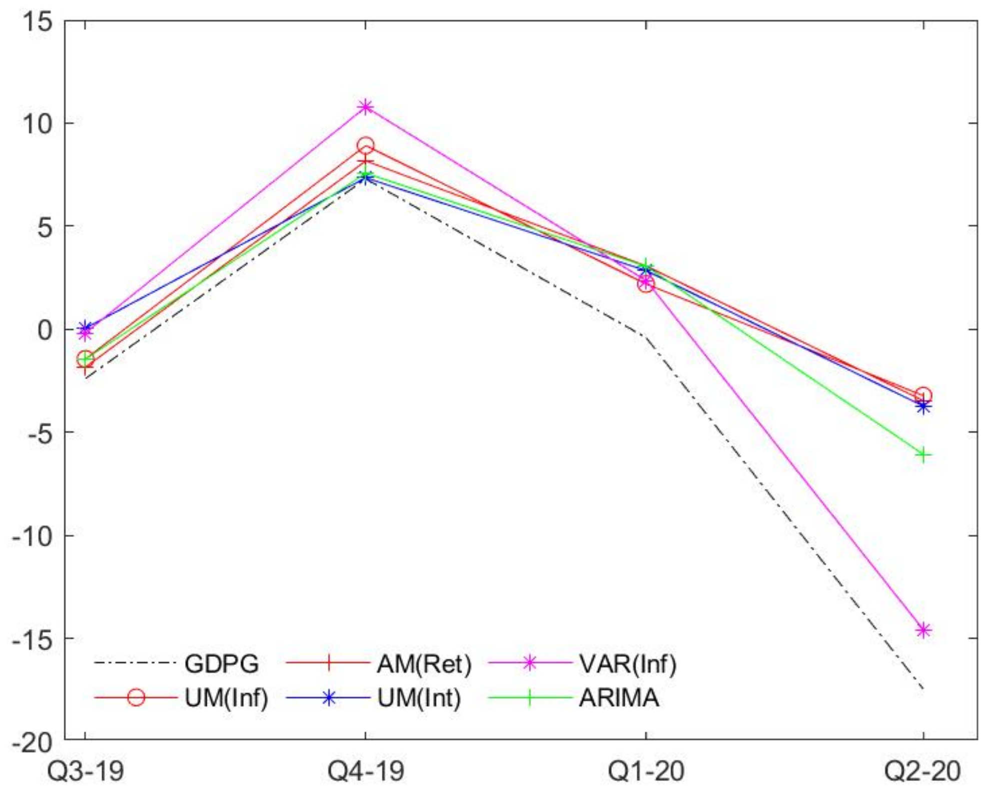


Figure 4: Real GDP Growth and Out-of-Sample Forecasts (in colors) from Various Models during Q3, 2019-Q2, 2020 (COVID)

## 4.2 Number of Workers in Labor Force

For the quarterly growth of the number of workers in labor force (or labor force growth) with no COVID data in the out-of-sample forecasts, the MIDAS with EAM using the daily change in interest rate and the VAR(4) using the monthly inflation seem to be the best two performing models where the MIDAS-EAM returns the lower MAPE while the VAR gives the lower RMSE. See more details in Tables 12-15. Across predictors, half of the MIDAS models using the change in interest rate result in the lower forecast errors while the results for the in-sample fit through AIC and BIC vary.

Table 12: Forecast Error Measures and Model Selection Criteria: Labor Force Growth with Inflation (No COVID)

| | MIDAS | | | | | | VAR(4) |
|---|---|---|---|---|---|---|---|
| | BT | BNN | EAM | UM | ST | AM | |
| MAPE | 739.20 | 745.04 | 744.80 | 707.44 | 979.24 | 945.75 | **326.75** |
| RMSE | 1.06 | 1.07 | 1.07 | 1.22 | 1.11 | 1.10 | **0.38** |
| DM-p | **0.96** | 0.94 | 0.95 | 0.60 | 0.81 | 0.82 | 0.76 |
| AIC | -13.66 | -11.72 | -13.84 | -6.41 | **-17.08** | -15.45 | 598.58 |
| BIC | 5.30 | 9.61 | 5.12 | 33.87 | **4.25** | 5.88 | 759.71 |

Table 13: Forecast Error Measures and Model Selection Criteria: Labor Force Growth with Stock Return (No COVID)

| | BT | BNN | EAM | UM | ST | AM |
|---|---|---|---|---|---|---|
| MAPE | 937.24 | 832.89 | 907.33 | 764.14 | **763.94** | 805.07 |
| RMSE | 1.08 | 1.09 | 1.08 | 1.07 | **1.06** | 1.07 |
| DM-p | 0.86 | 0.89 | 0.87 | **0.96** | 0.95 | 0.93 |
| AIC | -17.06 | -15.95 | -17.37 | -14.39 | **-19.45** | -16.10 |
| BIC | 1.90 | 5.38 | 1.58 | 9.30 | **-2.86** | 5.22 |

Table 14: Forecast Error Measures and Model Selection Criteria: Labor Force Growth with Change in Interest Rate (No COVID)

| | BT | BNN | EAM | UM | ST | AM |
|---|---|---|---|---|---|---|
| MAPE | 108.00 | 171.87 | **107.08** | 1,026.99 | 563.00 | 933.13 |
| RMSE | **0.74** | 0.90 | **0.74** | 1.16 | 0.79 | 1.01 |
| DM-p | 0.47 | 0.49 | 0.47 | 0.75 | 0.58 | **0.97** |
| AIC | -1.91 | 0.09 | -1.90 | 1.93 | **-2.64** | 0.30 |
| BIC | 9.56 | 13.00 | 9.57 | 16.27 | **7.40** | 13.21 |

Table 15: Forecast Error Measures and Model Selection Criteria: Labor Force Growth with Change in Foreign Exchange Rate (No COVID)

| | BT | BNN | EAM | UM | ST | AM |
|---|---|---|---|---|---|---|
| MAPE | 828.51 | 774.70 | 833.08 | 768.89 | **763.57** | 775.07 |
| RMSE | 1.12 | 1.08 | 1.12 | 1.07 | **1.05** | 1.07 |
| DM-p | 0.85 | 0.93 | 0.84 | 0.92 | **0.97** | 0.93 |
| AIC | -13.37 | -11.08 | -13.37 | -10.22 | **-16.20** | -12.15 |
| BIC | 5.59 | 10.24 | 5.58 | 13.48 | **0.38** | 9.17 |

In terms of forecast errors, the MIDAS with EAM using the daily change in interest rate and the VAR using the monthly inflation are still the best two forecasting models when comparing with the ARIMA model (Table 16 and Figures 5-6). The MIDAS with ST using the daily return is best for the in-sample analysis. Note that the quarterly labor force growth is known for its strong seasonality. This might be the reason why the monthly inflation through the VAR can return the forecasts that capture this seasonal pattern (Figure 6). While returning the lowest MAPE, the MIDAS with EAM using the change in interest rate return cannot predict the seasonality. Hence, the VAR might be the better forecasting model in this sense and provide more insight for the quarterly labor force growth.

Table 16: Comparison of Selected Results for Labor Force Growth (No COVID)

| | MIDAS-ST | MIDAS-EAM | MIDAS-ST | VAR(4) | ARIMA |
|---|---|---|---|---|---|
| | Return | Interest | Forex | Inflation | $(0,0,1)(0,1,1)_4$ |
| MAPE | 763.94 | **107.08** | 763.57 | 326.75 | 1,357.57 |
| RMSE | 1.06 | 0.74 | 1.05 | **0.38** | 1.04 |
| DM-p | 0.95 | 0.47 | **0.97** | 0.76 | 0.93 |
| AIC | **-19.45** | n.a. | -16.20 | 598.58 | 201.11 |
| BIC | **2.86** | n.a. | 0.38 | 759.71 | 207.90 |

Notes: ARIMA$(p,d,q)(P,D,Q)_m$ refers to $p$ lag orders of AR part, $d$ degrees of first differencing, $q$ lag orders of MA part, $P$ lag orders of seasonal AR part, $D$ degrees of seasonal first differencing, $Q$ lag orders of seasonal MA part, and $m$ seasonal periods, and n.a. = not available.

With the COVID data in the out-of-sample forecasts, the daily return and the daily change in the foreign exchange rate are two higher frequency variables that have the lower forecast errors (Table 17-20). This is also true for the in-sample fit through AIC

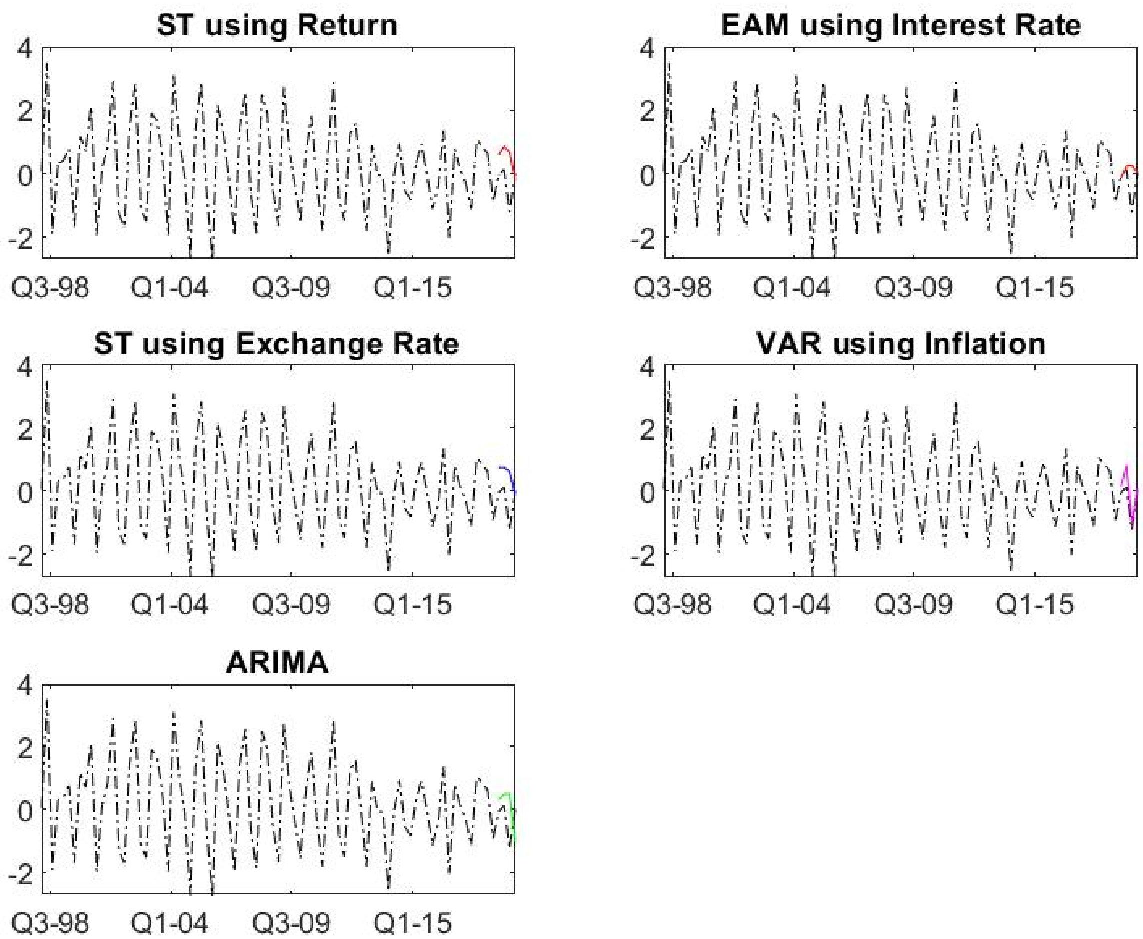


Figure 5: Labor Force Growth and Out-of-Sample Forecasts (in colors) from Various Models during Q1, 1998-Q4, 2019 (No COVID)

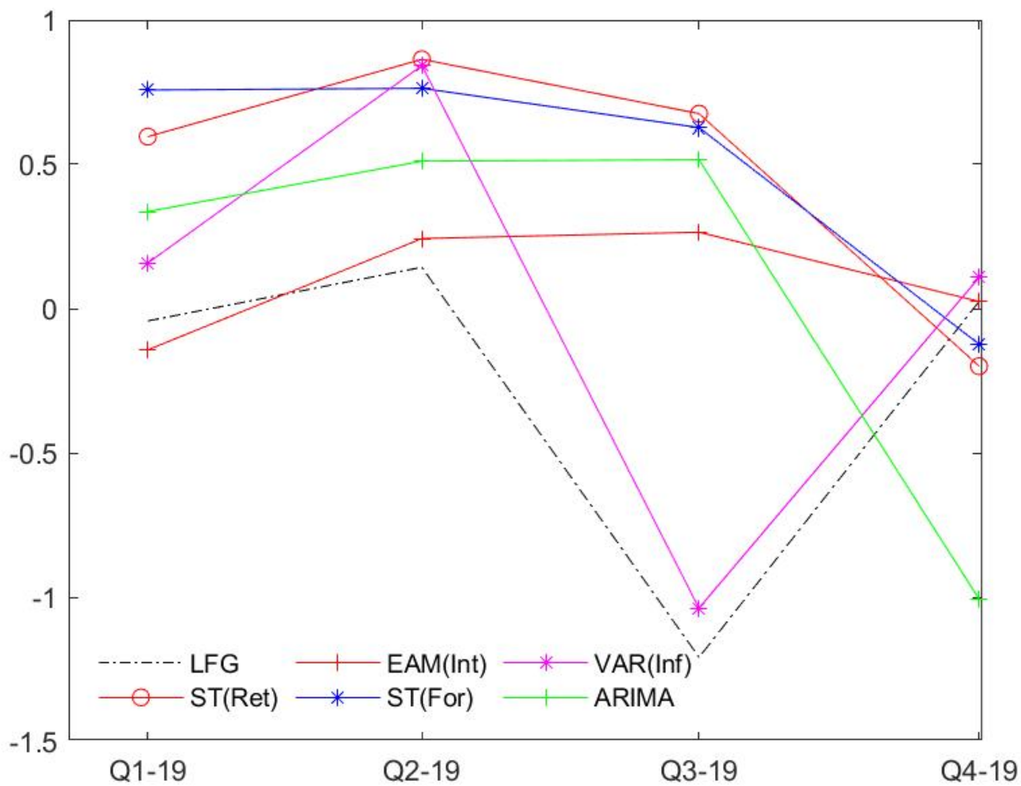


Figure 6: Labor Force Growth and Out-of-Sample Forecasts (in colors) from Various Models during Q1, 2019-Q4, 2019 (No COVID)

and BIC. The MIDAS with AM using the change in foreign exchange gives the lowest MAPE followed by the MIDAS with BNN using the daily return. In terms of RMSE, the MIDAS with ST using the daily change in interest rate is the best forecasting model for the quarterly labor force growth. VAR seems to be the worst performing as its forecast errors are quite high.

Table 17: Forecast Error Measures and Model Selection Criteria: Labor Force Growth with Inflation (COVID)

| | MIDAS | | | | | | VAR(4) |
|---|---|---|---|---|---|---|---|
| | BT | BNN | EAM | UM | ST | AM | |
| MAPE | 394.62 | 418.97 | **394.52** | 739.96 | 631.63 | 575.76 | 2,230.91 |
| RMSE | **0.94** | 0.95 | 0.95 | 1.24 | 0.97 | 0.95 | 1.24 |
| DM-p | 0.43 | 0.44 | 0.42 | **0.89** | 0.54 | 0.56 | 0.24 |
| AIC | -16.34 | -14.07 | -16.52 | -8.92 | **-19.72** | -18.06 | 607.95 |
| BIC | 2.81 | 7.48 | 2.64 | 31.79 | **1.83** | 3.49 | 770.77 |

Table 18: Forecast Error Measures and Model Selection Criteria: Labor Force Growth with Stock Return (COVID)

| | BT | BNN | EAM | UM | ST | AM |
|---|---|---|---|---|---|---|
| MAPE | 398.30 | **277.78** | 328.30 | 293.37 | 291.81 | 299.55 |
| RMSE | 0.95 | 0.95 | **0.93** | 0.96 | 0.94 | 0.95 |
| DM-p | **0.45** | 0.40 | 0.41 | 0.40 | 0.40 | 0.41 |
| AIC | -19.77 | -18.75 | -20.11 | -17.19 | **-22.22** | -18.90 |
| BIC | -0.62 | 2.80 | -0.95 | 6.75 | **-5.46** | 2.65 |

Table 19: Forecast Error Measures and Model Selection Criteria: Labor Force Growth with Change in Interest Rate (COVID)

| | BT | BNN | EAM | UM | ST | AM |
|---|---|---|---|---|---|---|
| MAPE | 811.28 | 905.86 | 818.00 | 726.76 | **419.81** | 678.91 |
| RMSE | 0.92 | 1.12 | 0.92 | 1.02 | **0.73** | 0.97 |
| DM-p | 0.70 | **0.91** | 0.70 | 0.65 | 0.40 | 0.54 |
| AIC | -4.88 | -2.69 | -4.87 | -1.10 | **-5.50** | -2.46 |
| BIC | 7.10 | 10.78 | 7.10 | 13.86 | **4.97** | 11.01 |

When the ARIMA model is taken into the consideration, the MIDAS with AM using daily foreign exchange and the MIDAS with ST using the interest are still the best forecasting models that return the lowest MAPE and RMSE, respectively (Table 21). These two models seem to move along well with the quarterly labor force growth

Table 20: Forecast Error Measures and Model Selection Criteria: Labor Force Growth with Change in Foreign Exchange Rate (COVID)

| | BT | BNN | EAM | UM | ST | AM |
|---|---|---|---|---|---|---|
| MAPE | 374.16 | 361.41 | 377.31 | 281.89 | 311.69 | **273.39** |
| RMSE | 0.98 | 0.95 | 0.98 | 0.92 | **0.90** | 0.92 |
| DM-p | **0.45** | 0.43 | **0.45** | 0.42 | 0.43 | 0.40 |
| AIC | -16.07 | -13.80 | -16.08 | -12.96 | **-18.94** | -14.89 |
| BIC | 3.08 | 7.75 | 3.08 | 10.99 | **-2.18** | 6.66 |

(Figures 7 and 8) The ARIMA is best only for the p-value from the DM test but its forecast errors are very high. The results might seem inconclusive regarding the forecasting model. However, one conclusion that can be made for the out-of-sample forecasts with COVID data is the higher frequency variables from the daily data return lower forecast errors.

One difficulty in dealing with the quarterly labor force growth is its strong seasonality. Under normal circumstances, e.g., no COVID pandemic, the VAR seems to handle well with the forecasts. This is also confirmed by Wichitaksorn *et al.* (2020) that use the VAR and structural VAR models to analyze the Thai labor market and found its slackness and tightness are highly related to the quarterly real GDP growth. With the shocks, forecasting the quarterly labor force growth needs careful consideration where higher-frequency daily variables might be a good candidate for that purpose. It is worth noting again for this case that the VAR with the daily data might be a good attempt but this is left for future research.

Table 21: Comparison of Selected Results for Labor Force Growth (COVID)

| | MIDAS-BT | MIDAS-BNN | MIDAS-ST | MIDAS-AM | ARIMA |
|---|---|---|---|---|---|
| | Inflation | Return | Interest | Forex | $(0,0,1)(0,1,1)_4$ |
| MAPE | 394.62 | 277.78 | 419.81 | **273.39** | 1,255.41 |
| RMSE | 0.94 | 0.95 | **0.73** | 0.92 | 1.12 |
| DM-p | 0.43 | 0.40 | 0.40 | 0.40 | **0.93** |
| AIC | -16.34 | **-18.75** | n.a. | -14.89 | 204.53 |
| BIC | 2.81 | **2.80** | n.a. | 6.66 | 211.40 |

Notes: ARIMA$(p,d,q)(P,D,Q)_m$ refers to $p$ lag orders of AR part, $d$ degrees of first differencing, $q$ lag orders of MA part, $P$ lag orders of seasonal AR part, $D$ degrees of seasonal first differencing, $Q$ lag orders of seasonal MA part, and $m$ seasonal periods, and n.a. = not available.

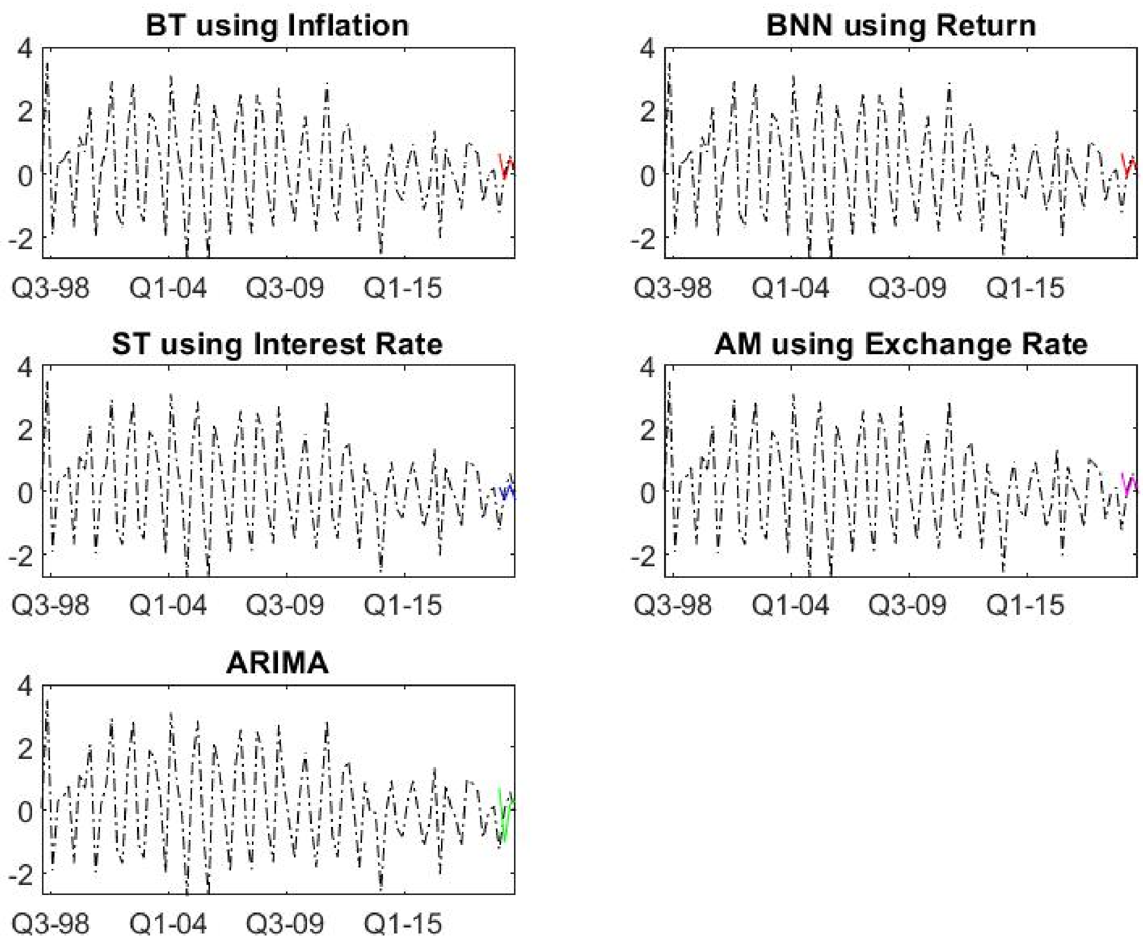


Figure 7: Labor Force Growth and Out-of-Sample Forecasts (in colors) from Various Models during Q1, 1998-Q2, 2020 (COVID)

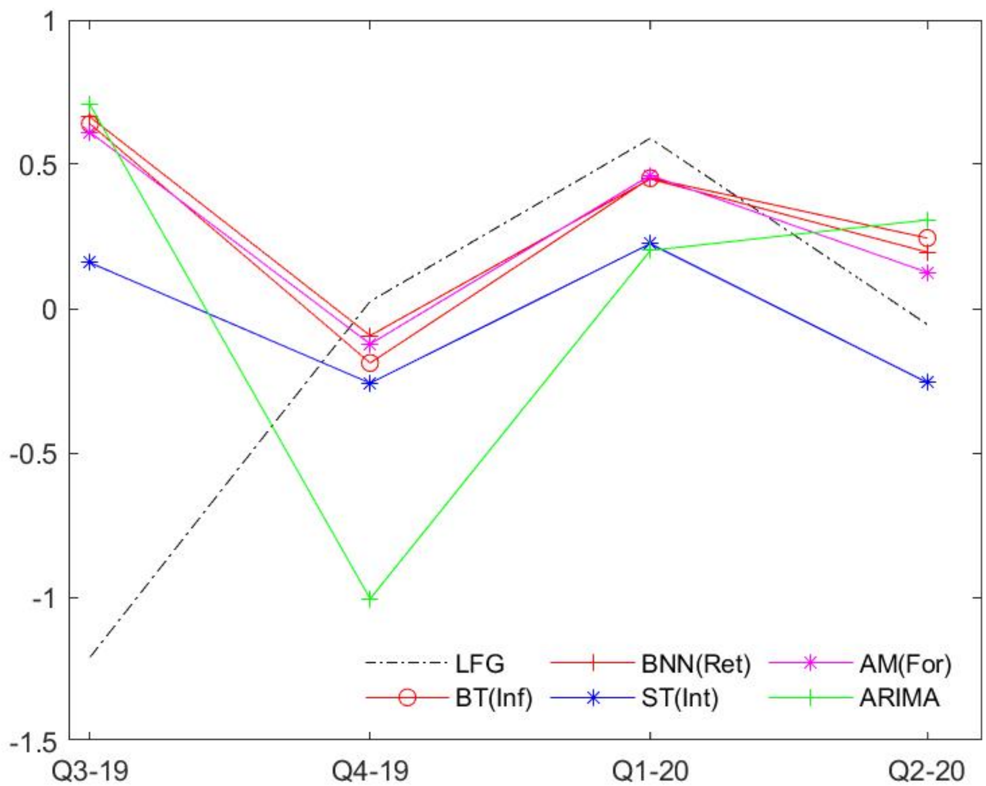


Figure 8: Labor Force Growth and Out-of-Sample Forecasts (in colors) from Various Models during Q3, 2020-Q2, 2020 (COVID)

## 4.3 Inflation

In this case, since the lower-frequency dependent variable is monthly (inflation), the only relevant higher-frequency variables are daily and include stock return, change in interest rate, and change in foreign exchange rate. Similar to other cases and due to the data availability, the start dates in the estimation are re-adjusted following the lag orders of the time series used. With the monthly inflation and to complete the seasonal pattern, the out-of-sample forecasts are 12 months, which are used in the forecasting evaluation.

Table 22-24 show the forecasting results from the MIDAS model with various specifications for the out-of-sample forecasts with no COVID data (Jan.-Dec. 2019). The MIDAS with ST seems to be the best performing model as it returns the lower forecast errors for at least two out of three higher-frequency predictors (daily return and change in interest rate). Among three predictors, the change in interest rate gives the lowest forecast errors across the measures (MAPE and RMSE) and the higher p-value from the DM test for most cases. Regarding the in-sample fit, the daily return is the best one for those criteria (AIC and BIC).

Table 22: Forecast Error Measures and Model Selection Criteria: Inflation with Stock Return (No COVID)

| | BT | BNN | EAM | UM | ST | AM |
|---|---|---|---|---|---|---|
| MAPE | 57.73 | 57.08 | 58.09 | 58.17 | **56.79** | 57.18 |
| RMSE | 0.33 | 0.33 | 0.33 | **0.32** | 0.33 | 0.33 |
| DM-p | 0.56 | 0.57 | 0.57 | **0.58** | 0.56 | 0.56 |
| AIC | -391.02 | -389.85 | -391.02 | -385.89 | **-391.95** | -390.18 |
| BIC | -328.36 | -323.28 | -328.36 | -307.57 | **-329.29** | -323.61 |

Table 23: Forecast Error Measures and Model Selection Criteria: Inflation with Change in Interest Rate (No COVID)

| | BT | BNN | EAM | UM | ST | AM |
|---|---|---|---|---|---|---|
| MAPE | 54.04 | 58.00 | 53.04 | 55.23 | **52.67** | 55.76 |
| RMSE | 0.32 | 0.33 | **0.31** | 0.32 | **0.31** | 0.32 |
| DM-p | 0.84 | 0.86 | 0.86 | 0.81 | **0.95** | 0.81 |
| AIC | -201.73 | -198.71 | -201.83 | -198.61 | **-202.84** | -200.61 |
| BIC | -160.87 | -155.29 | -160.96 | -152.64 | **-164.53** | -157.19 |

To make a fair comparison, the ARIMA model was estimated with different start dates corresponding to those of daily variables. Hence, we found the ARIMA model

Table 24: Forecast Error Measures and Model Selection Criteria: Inflation with Change in Foreign Exchange Rate (No COVID)

| | BT | BNN | EAM | UM | ST | AM |
|---|---|---|---|---|---|---|
| MAPE | 58.86 | 60.33 | 58.67 | 59.48 | 61.01 | **58.57** |
| RMSE | 0.34 | 0.34 | 0.34 | 0.34 | 0.34 | **0.33** |
| DM-p | 0.71 | 0.66 | 0.71 | **0.85** | 0.65 | 0.77 |
| AIC | -373.10 | -366.30 | -373.04 | **-373.60** | -370.10 | -370.80 |
| BIC | -312.07 | -301.46 | -312.01 | -304.94 | **-312.89** | -305.96 |

with the same start date and length of data as those of daily change in foreign exchange rate returns the best results in terms of forecast error measures. However, the ARIMA as the benchmark model is still outperformed by all MIDAS models in most of the measures and criterion (Table 25 and Figures 9-10). The MIDAS with ST using the daily change in interest rate is the best forecasting model as it returns the lowest forecast errors.

The results imply that without the COVID pandemic the inflation responds well with the change in interest rate. This provides a meaningful economic implication. The interest rate can be an effective policy instrument to control the inflation, especially if the Bank of Thailand uses inflation targeting as one of the tools for macroeconomic management.

Table 25: Comparison of Selected Results for Inflation (No COVID)

| | MIDAS-ST | MIDAS-ST | MIDAS-AM | ARIMA |
|---|---|---|---|---|
| | Return | Interest | Forex | $(1,1,1)(2,0,2)_{12}$ |
| MAPE | 56.79 | **52.67** | 58.57 | 110.20 |
| RMSE | 0.33 | **0.31** | 0.33 | 0.39 |
| DM-p | 0.56 | **0.95** | 0.77 | 0.96 |
| AIC | **-391.95** | n.a. | -370.80 | 470.07 |
| BIC | **-329.29** | n.a. | -305.96 | 496.43 |

Notes: ARIMA$(p,d,q)(P,D,Q)_m$ refers to $p$ lag orders of AR part, $d$ degrees of first differencing, $q$ lag orders of MA part, $P$ lag orders of seasonal AR part, $D$ degrees of seasonal first differencing, $Q$ lag orders of seasonal MA part, and $m$ seasonal periods, and n.a. = not available.

When the COVID data are included in the out-of-sample forecasts, the daily change in interest rate is still the best forecasting predictor for all MIDAS models. This emphasizes the role of interest rate even in an awkward situation. The daily return is best

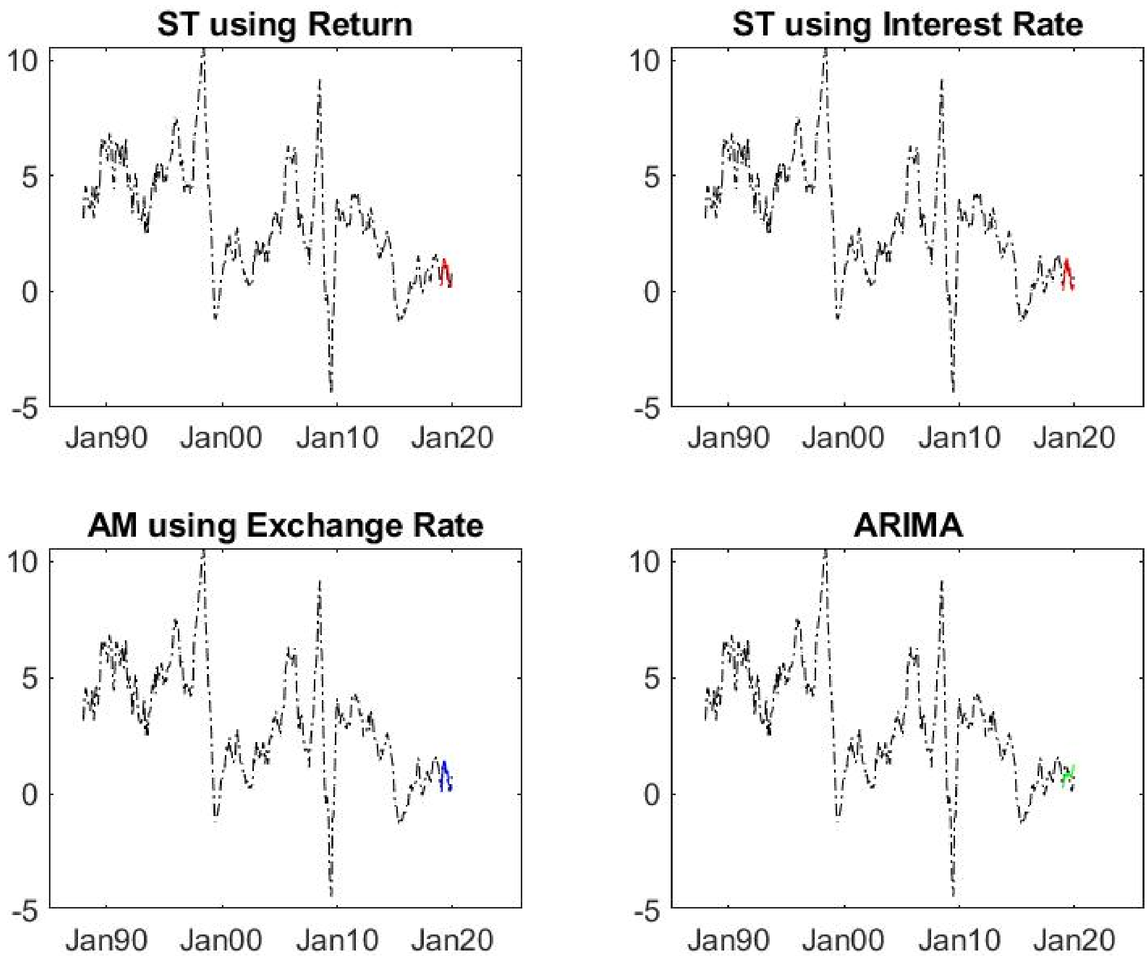


Figure 9: Inflation and Out-of-Sample Forecasts (in colors) from Various Models during Jan. 1998-Dec. 2019 (No COVID)

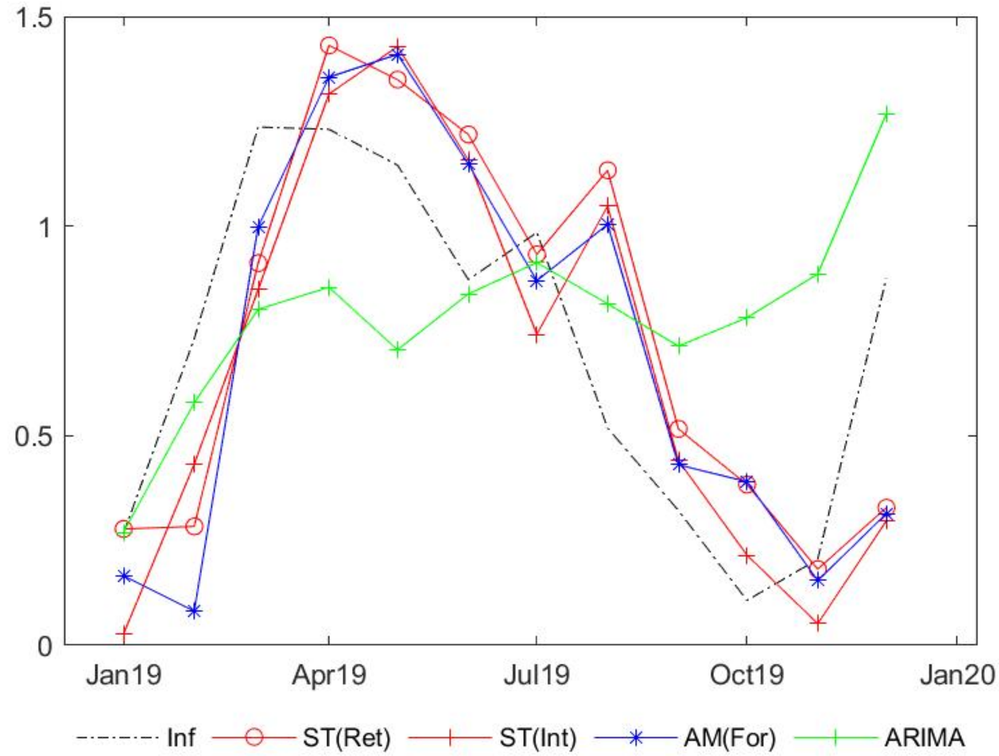


Figure 10: Inflation and Out-of-Sample Forecasts (in colors) from Various Models during Jan. 2019-Dec. 2019 (No COVID)

in terms of p-value from the DM test and in-sample fit but all of its MIDAS models give higher forecast errors.

With the COVID data in out-of-sample forecasts, the ARIMA model with the same start date as that of the daily interest rate gives the best forecasting results and was chosen to compare with other MIDAS models. According to Table 29, it seems that the ARIMA model outperforms all MIDAS models in terms of forecast errors while the MIDAS with BNN using the daily return is best for the p-value from the DM test and the in-sample fit but it gives the high forecast errors. However, we found Figure 8 that the MIDAS models tend to capture the inflation pattern better than the ARIMA, especially from Jan. 2020 where the COVID-19 pandemic started. Note that the MIDAS model with BNN using the change in interest rate can even follow the inflation when it recovered in Jun. 2020. The ARIMA model returns the symmetric forecasts, which on average are close to the real data. This is why it gives lower forecast errors. Hence, it is worth to re-attempt this analysis again when the COVID-19 pandemic finishes. Our preliminary conclusion in this case is the MIDAS model using the daily

Table 26: Forecast Error Measures and Model Selection Criteria: Inflation with Stock Return (COVID)

| | BT | BNN | EAM | UM | ST | AM |
|---|---|---|---|---|---|---|
| MAPE | 85.68 | **84.37** | 86.92 | 85.08 | 84.50 | 85.45 |
| RMSE | 1.00 | 0.97 | 1.01 | **0.96** | 0.97 | 0.98 |
| DM-p | **0.80** | **0.80** | 0.77 | **0.80** | **0.80** | **0.80** |
| AIC | -381.70 | -383.20 | -381.70 | -379.80 | **-385.23** | -383.18 |
| BIC | -318.79 | -316.36 | -318.79 | -301.16 | **-322.31** | -316.33 |

Table 27: Forecast Error Measures and Model Selection Criteria: Inflation with Change in Interest Rate (COVID)

| | BT | BNN | EAM | UM | ST | AM |
|---|---|---|---|---|---|---|
| MAPE | 75.26 | **71.09** | 73.88 | 73.95 | 72.11 | 76.09 |
| RMSE | 0.97 | **0.94** | 0.96 | 0.98 | 0.94 | 0.98 |
| DM-p | 0.61 | **0.63** | 0.61 | 0.56 | **0.63** | 0.59 |
| AIC | -166.97 | -164.45 | -166.96 | -163.00 | **-168.57** | -164.97 |
| BIC | -125.12 | -119.99 | -125.12 | -115.92 | **-129.34** | -120.52 |

Table 28: Forecast Error Measures and Model Selection Criteria: Inflation with Change in Foreign Exchange Rate (COVID)

| | BT | BNN | EAM | UM | ST | AM |
|---|---|---|---|---|---|---|
| MAPE | 86.99 | 90.18 | 87.07 | 85.77 | 90.06 | **85.33** |
| RMSE | 1.04 | **1.02** | 1.04 | 1.05 | **1.02** | **1.02** |
| DM-p | 0.71 | 0.70 | 0.71 | **0.75** | 0.70 | 0.74 |
| AIC | **-360.82** | -356.04 | -360.80 | -359.92 | -360.00 | -359.22 |
| BIC | -299.51 | -290.89 | -299.49 | -290.95 | **-302.52** | -294.08 |

change in interest rate still performs well and provides a useful economic implication.

Table 29: Comparison of Selected Results for Inflation (COVID)

| | MIDAS-BNN | MIDAS-BNN | MIDAS-AM | ARIMA |
|---|---|---|---|---|
| | Return | Interest | Forex | $(1,1,0)(0,0,1)_{12}$ with drift |
| MAPE | 84.37 | 71.09 | 85.33 | **40.78** |
| RMSE | 0.97 | 0.94 | 1.02 | **0.24** |
| DM-p | **0.80** | 0.63 | 0.74 | 0.02 |
| AIC | **-383.20** | n.a. | -359.22 | 35.31 |
| BIC | **-316.36** | n.a. | -294.08 | 45.35 |

Notes: ARIMA$(p,d,q)(P,D,Q)_m$ refers to $p$ lag orders of AR part, $d$ degrees of first differencing, $q$ lag orders of MA part, $P$ lag orders of seasonal AR part, $D$ degrees of seasonal first differencing, $Q$ lag orders of seasonal MA part, and $m$ seasonal periods, and n.a. = not available.

# 5 Conclusions

This study aims to analyze and forecast some Thai macroeconomic variables using the mixed-frequency approach. The mixed-frequency models used include the MIDAS with various specifications and the VAR where their forecasting results are compared with those of ARIMA that is used as the benchmark model. The macroeconomic data used as the lower-frequency dependent variable in the forecasting are the quarterly real GDP growth, the quarterly labor force growth, and the monthly inflation, where the monthly inflation, the daily stock return, the daily change in interest rate, and the daily change in foreign exchange rate are used as the higher-frequency predictor. The data are split into the COVID and non-COVID out-of-sample periods to assess the performance of the models.

We found that most of the mixed-frequency models, either MIDAS or VAR, outperform the ARIMA in terms of the forecast error measures except for the case of monthly inflation with the COVID data. Some implications from this study are (1) the daily returns (through the MIDAS) and the monthly inflation (through the VAR) are a good predictor for the real GDP growth and can provide some economic insights, (2) the unique characteristics of Thai labor market with the strong seasonality and the slackness and the tightness following the real GDP growth need to be explored further, and (3) under normal circumstances the daily interest rate seems to be an effective

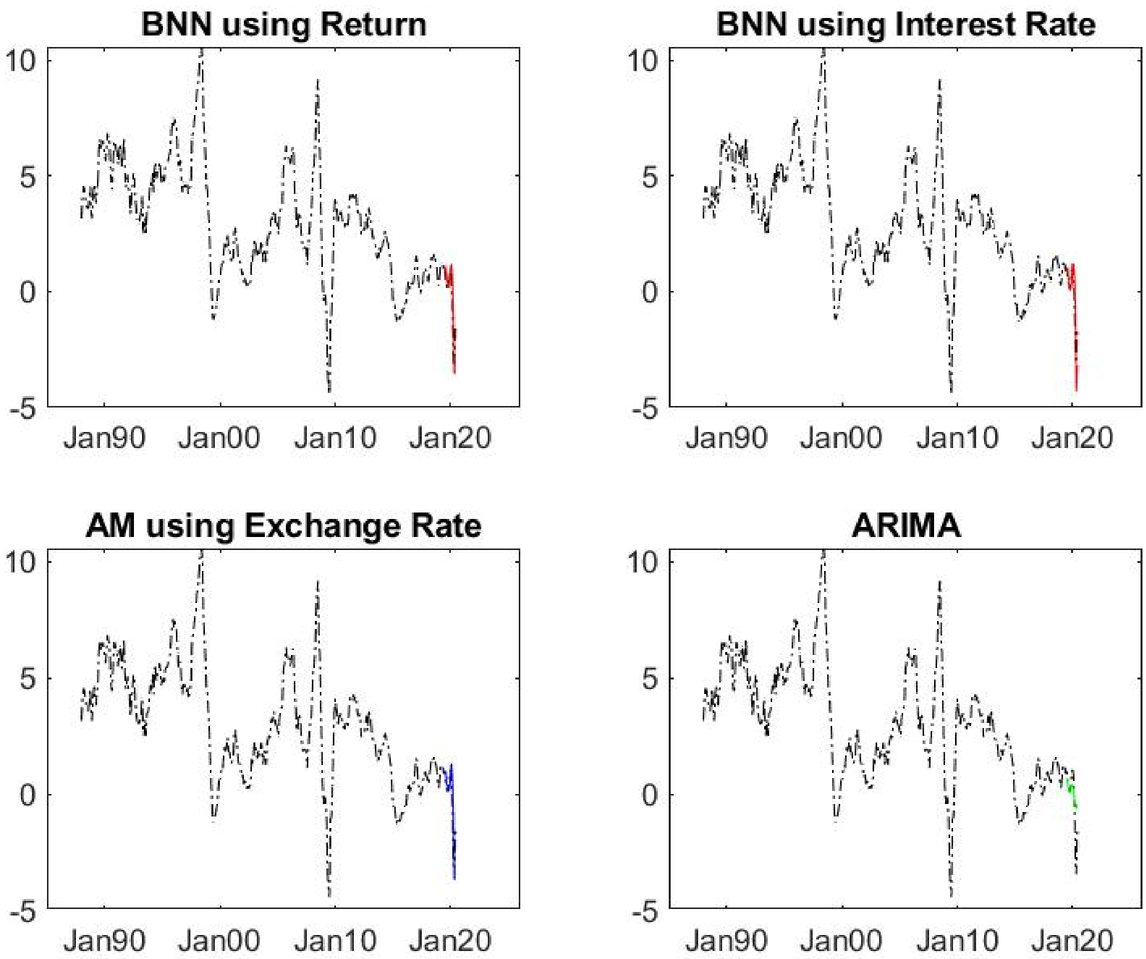


Figure 11: Inflation and Out-of-Sample Forecasts (in colors) from Various Models during Jan. 1998-Jun. 2020 (COVID)

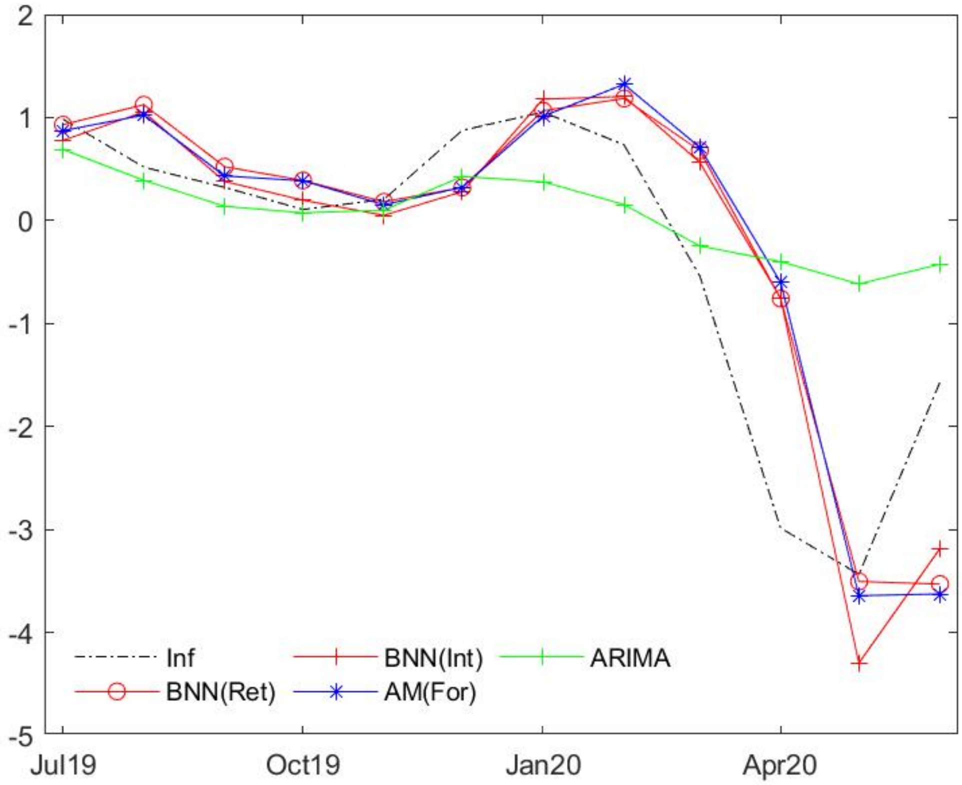


Figure 12: Inflation and Out-of-Sample Forecasts (in colors) from Various Models during Jul. 2019-Jun. 2020 (No COVID)

instrument to control the inflation. Based on the results, the extension of the VAR to the higher-frequency variables such as the daily data and the assessment of all models after the end of COVID pandemic are worth attempting as future research.

# Acknowledgments


This project was financially supported by a research grant from Puey Ungphakorn Institute for Economic Research, which I am very grateful to.


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