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Forecasting Macroeconomic Variables in Emerging Economies: An Application to Vietnam

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ABSTRACT

Forecasting macroeconomic variables in the rapidly changing macroeconomic environments faced by developing and emerging countries is an important task for central banks and policy-makers, yet often presents a number of challenges. In addition to the structural changes in the economy, the time-series data are usually available only for a small number of periods, and predictors are available in different lengths and frequencies. Dynamic model averaging (DMA), by allowing the forecasting model to change dynamically over time, permits the use of predictors with different lengths and frequencies for the purpose of forecasting in a rapidly changing economy. This study uses DMA to forecast inflation and growth in Vietnam, and compares its forecasting performance with a wide range of other time-series methods. Some results are noteworthy. First, the number and composition of the optimal predictor set changed, indicating changes in the economic relationships over time. Second, DMA frequently produces more accurate forecasts than other forecasting methods for both the inflation and the economic growth rate of Vietnam.

Keywords: Bayesian, dynamic model averaging, forecasting macroeconomic variables, Vietnam

JEL Classification: E31, E37, O40, C11, C53

1 Introduction

Policymakers and market participants have paid continuous attention to forecasting macroeconomic variables but face the challenge of structural breaks, as relationships among macroeconomic variables tend to change over time. Dynamic model averaging (DMA), which was first introduced by Raftery, Karny, and Ettler (2010), appears to be an ideal tool in forecasting macroeconomic variables, as it allows for the forecasting model to change dynamically over time. There are a number of studies that apply DMA for forecasting inflation and economic growth rates of advanced economies (Koop and Korobilis, 2012; Nicoletti and Passaro, 2012; Filippo, 2015).

DMA is also expected to be an accurate forecasting method for macroeconomic variables of developing economies, which tend to have more structural breaks than the variables of advanced economies. Among the reasons is that developing economies are expected to experience a more dynamic economic growth path and more frequent changes in policy and legal framework than developed economies. Moreover, most of developing countries, including Vietnam, are small open economies, which are sensitive to external shocks from the global economy or influential economies, such as the global financial crisis in 2008, the European sovereign debt crisis in 2010, and the structural changes in China's economy in recent years. With all the shocks which can come from both inside and outside of the economy, the relationships among macroeconomic variables of a developing economy are likely to change over time and DMA can deal with this dynamism by allowing both the forecasting model and the parameters to change over time.

Another difficulty related to the macroeconomic data of developing countries is that the time series data are usually available only for a relatively small number of periods, which means that less information is utilized in forecasting. Moreover, the available time-series may have different lengths and frequencies; this makes utilizing the data even more difficult. However, by allowing the forecasting model to change dynamically over time, DMA can address those problems. For example, for a variable whose data are missing at some points in time, DMA does not use the model with missing data. However, when the data become available, the model containing that variable would be used, as DMA dynamically rotates among the models. In addition, even time-series with different frequencies can be utilized, since DMA employs the available information, regardless of the frequency, at the time the forecast is made. Therefore, DMA can employ all possible predictors.

With all the difficulties in forecasting macroeconomic variables in developing countries and the desirable properties that DMA offers to deal with those challenges, there is a strong motivation to apply DMA in forecasting inflation and economic growth rates in Vietnam. This study applied DMA in forecasting inflation and economic growth rates at 1-month, 6-month, and 12-month horizons. By comparing root mean square errors (RMSEs), this study found that DMA generally produces more accurate forecasts of both inflation and economic growth rates than other forecasting methods. Moreover, the results show that even in the unexpected scenario of economic downturn due to the Covid-19 pandemic, using data up to 2019, DMA still forecasts quite well the future inflation and economic growth rates of Vietnam in 2020. The realized values of inflation and economic growth rates for 1-month and 6-month horizons are generally inside the 95% credible intervals computed by DMA.

The rest of this paper is organized as follows. Literature review is presented in Section 2, while Section 3 introduces the methodology. Section 4 presents details on the data employed in the forecasting model. Section 5 presents the forecasting results. Finally, Section 6 concludes with policy implications and avenues for future research.

2 Literature Review

There is a growing body of literature on forecasting inflation and economic growth rates, owing to the importance of forecasting these variables for both policymakers and market participants. More recent works have applied more advanced econometric techniques in an attempt to find a suitable forecasting model. The literature on forecasting inflation can be considered to start with studies that applied the Phillips curve single-equation model, of which Stock and Watson (1999) is a representative study. Stock and Watson (1999) generalized the Phillips curve equation to forecast the US inflation rate at a 12-month horizon. Using monthly data from January 1959 to September1997, the authors found that their forecasting model with a new activity index composed of 168 economic indicators outperformed the other Phillips curve-based models. However, Atkeson and Ohanian (2001) checked the accuracy of several fashionable Phillips curve-based inflation forecasts at that time, including that of Stock and Watson (1999), a non-accelerating inflation rate of unemployment model, and the Federal Reserve's model, and found that none performed better than a naive forecast for the data from 1984. This empirical result relates to the monetary policy change in the US in the early 1980s, which led the changing relationships among macroeconomic variables, and therefore, a fixed regression model could no longer produce accurate forecasts. A monetary policy change was shown by Clarida, Gali, and Gertler (2000) under the Volcker–Greenspan period, when the Federal fund rate was seen to be more sensitive to inflation expectations than in the previous period.

Since the fixed model no longer is suitable for forecasting inflation in the context of changing monetary policy or other changes in economic environment, the time-varying parameter (TVP) model has been used to develop a better forecast model. Cogley, Morozov, and Sargent (2005) were among the first to apply the TVP model to forecasting inflation. They applied Bayesian vector-autoregression (BVAR) with TVP to forecast the UK inflation rate. The model was found to be comparable with the forecasting method used by the Bank of England. Moreover, Green, Paap, and Ravazzolo (2013) applied Bayesian model averaging (BMA) with TVP to forecast the US inflation rate from 1960 to 2011, and proved that the model produced an accurate forecast, especially after 1984. Previous studies have found that 1984 marked a change in the Federal fund rate reaction rule and that the Phillips curve-based forecast is not better than the naive forecast (Clarida, Gali, and Gertler, 2000; Atkeson and Ohanian, 2001).

The TVP model has so far proved its appropriateness for forecasting inflation. The applied TVP model in the literature has become more complicated, as researchers seek to build a forecast model that is flexible enough to capture changing relationships among inflation and its predictors. Although applying a complicated TVP model can produce a better forecast model, its computational cost also increases. In this context, Koop and Korobilis (2012) were the first to apply DMA, the method was first introduced by Raftery, Karny, and Ettler (2010). DMA first allows for both a changing model and changing parameters, which are the desirable properties for designing a forecast model for inflation. Second, by using two forgetting factors, DMA reduces the computational cost and makes it more feasible to build a flexible forecast model for inflation. Using quarterly data of the US inflation rate from 1960 to 2008, DMA was found to produce accurate forecasts for the US inflation rate at horizons of 1 quarter, 1 year, and 2 years. Later, Filippo (2015) applied DMA to forecast inflation rates of the US and Euro area. Based on a sample from 1980 to 2012, DMA was proved to provide good inflation forecasts in both economies. These studies also compared DMA with other forecasting methods, including autoregression and TVP models, and its forecasting performance was generally found to be better than the others.

The literature review easily shows that DMA has been proved to be a competent choice in forecasting the inflation rate, among other complicated models. More broadly, its properties make it fit not only for inflation forecasts but also forecasts of other macroeconomic variables, including economic growth. Although there are not as many applications of DMA for economic growth forecasts as for inflation forecasts, DMA has been found to produce accurate forecasts of economic growth in the studies in which it has been applied. Among them, Nicoletti and Passaro (2012) applied DMA to forecast Italian GDP growth from 1990 to 2009. The method was proved to be an ideal tool for identifying good predictors of Italian economic growth in different periods. Specifically, bank credit spread was found to be a good predictor in a recession period, while government bond yield spread was found to be a good predictor in a period of economic stability.

Despite its increasing popularity in forecasting macroeconomic variables of developed countries, there are few applications of DMA to developing countries. This is the first work to apply DMA for forecasting inflation and economic growth in Vietnam in particular. Previously, several works have used different methods. Nguyen and Tran (2015) investigated the accuracy of forecasting inflation by the autoregressive integrated moving average (ARIMA), Grey model (GM) and the discrete Grey model (DGM), among other models. The study was based on several inflation measurements, including the consumer price index (CPI), raw material price, and gold price. Using the monthly data from January 2005 to November 2013, the study found that while ARIMA produces a good forecast for the raw material price and gold price, both GM(1,1) and DGM(1,1) produce a good forecast for the CPI. Later, Tran (2017) used a wide range of univariate models and vector autoregression (VAR) models to forecast the Vietnamese inflation rate. The study found that AR(6) is the best model for forecasting the quarterly inflation rate, and a VAR model which includes inflation rate, interest rate, exchange rate, and real retail sales is the best model for forecasting the monthly inflation rate. Generally, from these studies, univariate models, including AR, ARIMA, and GM, seem to be reliable for forecasting Vietnamese inflation. These empirical results suggest that past values of the inflation rate are a good predictor of the future inflation rate of Vietnam.

This study makes several contributions to the literature. First, we contribute to the literature that applies DMA to developing countries. Based on the advantages that DMA offers to deal with structural breaks in the relationship among macroeconomic variables, its application in developing countries is expected to be very promising, yet there are very few studies that do so. Second, ours is the first work to apply DMA to forecasting inflation and economic growth in Vietnam. Thus, this study contributes not only to the literature but also to the conduct of monetary policy of the State Bank of Vietnam (SBV) and other relevant public policies of the Vietnamese government.

3 Methodology

3.1 Dynamic Model Averaging and Dynamic Model Selection

Both DMA and dynamic model selection (DMS) consider K models which have different subsets of predictors $z_t^{(k)}$[1], where $z_t^{(k)}$ is a vector of predictors and $\theta_t^{(k)}$ are time-varying coefficients in model k for $k = 1, 2, ..., K$. Therefore, the standard set-up follows Raftery, Karny, and Ettler (2010):

$$y_t = z_t^{(k)}\theta_t^{(k)} + \epsilon_t^{(k)}. \tag{1}$$

$$\theta_{t+1}^{(k)} = \theta_t^{(k)} + \eta_t^{(k)}.^{2} \tag{2}$$

With $\epsilon_t^{(k)} \sim N(0, H_t^{(k)})$ and $\eta_t^{(k)} \sim N(0, Q_t^{(k)})$. Let $L_t \in \{1, 2, ..., K\}$ denote the true model at time t, $\pi_{t|t-1,k} = Pr(L_t = k|Y_{t-1})$ is the probability that model k is true model at time t, given the information up to time $t-1$ ($Y_{t-1} = \{y_1, y_2, ..., y_{t-1}\}$). DMA then does model averaging and specifies the fitted value of the dependent variable as:

$$\hat{y}_t^{DMA} = \sum_{k=1}^{K} \pi_{t|t-1,k} z_t^{(k)} \hat{\theta}_{t-1}^{(k)}. \tag{3}$$

On the other hand, DMS selects the predicting result of the best model k^*, which has the highest $\pi_{t|t-1,k^*}$, for each point in time.

$$\hat{y}_t^{DMS} = z_t^{(k^*)} \hat{\theta}_{t-1}^{(k^*)}. \tag{4}$$

It is easy to observe that with m predictors, the number of models considered at each point in time is $K = 2^m$, as all the possible combinations of m predictors are counted. With a large m, the procedure requires high computational power. Therefore, following Raftery, Karny, and Ettler (2010), the procedure is simplified by applying two

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[1] $z_t^{(k)}$ includes predictors available at time t. This means that $z_t^{(k)}$ contains lags of all regressors up to period $t-1$. y_t is defined as in Section 4 as either inflation in period t, or average inflation between periods t and $t+h$. To take into account the persistence and seasonality of the data, first, the lag and the lag of the same month in the previous year of dependent variable y_t are included in the group of predictors.

[2] Theoretically, it is possible not to assume a random walk for $\theta_t^{(k)}$; for example, it can be a stationary process. However, as the changes in $\theta_t^{(k)}$ reflect structural changes in parameters, these do not need to revert to a historical mean like a stationary process. Therefore, in this literature, it is common to use a random walk transition equation for the parameters. Moreover, making $\theta_t^{(k)}$ a stationary process means that we have to estimate one more parameter and it is not clear that the forecast would improve for this reason. Indeed, this method aims to simplify the computation, so it is reasonable to use a random walk for $\theta_t^{(k)}$.

forgetting factors α and λ $(0 < \alpha, \lambda \leq 1)$. First, λ plays a role in calculating $\theta_{t-1}^{(k)}$. For a specific model k with TVPs, Kalman filtering can be applied to carry out the recursive forecasting as follows:

$$\theta_{t-1|t-1}^{(k)} \sim N(\hat{\theta}_{t-1}^{(k)}, \textstyle\sum_{t-1|t-1}^{(k)}). \qquad (5)$$

$$\theta_{t|t-1}^{(k)} \sim N(\hat{\theta}_{t-1}^{(k)}, \textstyle\sum_{t|t-1}^{(k)}). \qquad (6)$$

Where

$$\textstyle\sum_{t|t-1}^{(k)} = \sum_{t-1|t-1}^{(k)} + Q_t^{(k)}. \qquad (7)$$

However, when λ is applied, the equation (7) is simplified to:

$$\textstyle\sum_{t|t-1}^{(k)} = \frac{1}{\lambda} \sum_{t-1|t-1}^{(k)}. \qquad (8)$$

The estimation of model k's parameters are then obtained by the updating equations as follows:

$$\theta_{t|t}^{(k)} \sim N(\hat{\theta}_t^{(k)}, \textstyle\sum_{t|t}^{(k)})$$

$$\hat{\theta}_t^{(k)} = \hat{\theta}_{t-1}^{(k)} + \textstyle\sum_{t|t-1}^{(k)} z_t^{(k)}(H_t^{(k)} + z_t^{(k)} \sum_{t|t-1}^{(k)} z_t^{(k)\prime})^{-1}(y_t - z_t^{(k)}\hat{\theta}_{t-1}^{(k)})$$

$$\textstyle\sum_{t|t}^{(k)} = \sum_{t|t-1}^{(k)} - \sum_{t|t-1}^{(k)} z_t^{(k)}(H_t^{(k)} + z_t^{(k)} \sum_{t|t-1}^{(k)} z_t^{(k)\prime})^{-1} z_t^{(k)} \sum_{t|t-1}^{(k)}$$

The forgetting factor λ can be interpreted as follows: observations j for periods in the past have weight λ^j in calculating the prediction. For example, when $\lambda = 0.99$, monthly data suggest that observations 3 years ago receive approximately 70% as much weight as last month's observations. Meanwhile, with $\lambda = 0.95$, observations 3 years ago receive only approximately 16% as much weight as last month's observations. Therefore, on the one hand, lower λ suggests the parameters change more quickly; on the other hand, higher λ suggests the parameters change more slowly.

For the case of multiple models, α is applied and simplifies the probability, given information up to time $t-1$, of model k as:

$$\pi_{t|t-1,k} = \frac{\pi_{t-1|t-1,k}^{\alpha}}{\sum_{l=1}^{K} \pi_{t-1|t-1,l}^{\alpha}}. \qquad (9)$$

The updating equation is:

$$\pi_{t|t,k} = \frac{\pi_{t|t-1,k} P_k(y_t|Y_{t-1})}{\sum_{l=1}^{K} \pi_{t|t-1,l} P_l(y_t|Y_{t-1})}$$

$P_l(y_t|Y_{t-1})$ is the predictive density (it can be normal density) for model l evaluated at y_t. The forgetting factor α can be interpreted as follows: if model k forecast well in the recent past, it would receive more weight in forecasting at the present time. For example, with monthly data, $\alpha = 0.99$ suggests that forecast performance 3 years ago receives 70% as much weight as forecast performance last month. Meanwhile, with $\alpha = 0.95$, forecast performance 3 years ago receives only 16% as much weight as forecast performance last month. Therefore, on the one hand, lower α suggests the forecasting models change more quickly; on the other hand, higher α suggests the forecasting models change more slowly. When setting $\alpha = \lambda = 1$, DMA becomes BMA in which both the weight and coefficients of each model do not change over time.

Regarding error variance $H_t^{(k)}$, Raftery, Karny, and Ettler (2010) applied homoskedastic error variance $H_t^{(k)} = H^{(k)}$, while Koop and Korobilis (2012) applied the exponentially weighted moving average (EWMA) estimate of $H_t^{(k)}$:

$$\hat{H}_t^{(k)} = \sqrt{(1-\kappa)\sum_{j=1}^{t} \kappa^{j-1}(y_j - z_j^{(k)}\hat{\theta}_j^{(k)})^2} \text{ , with } \kappa \text{ is decay factor}$$

The application of EWMA is observed more in the finance field than in the economics field, as researchers in the former field usually deal with long time-series data with more frequent fluctuation than economic data. However, the data used in this study cannot be viewed as long data with less than 300 observations. Moreover, this study runs the regression in the cases of both applying EWMA and homoskedastic error variance ($H_t^{(k)} = H^{(k)}$), and finds no significant difference in forecasting performance between these two regressions, indicated by RMSE. Therefore, this study introduces the regression assuming $H_t^{(k)} = H^{(k)}$ as the main result.

3.2 Other forecasting methods

Other forecasting methods are introduced in this study for comparison with the forecasting performance of DMA and DMS. First, the naive forecast is used, whereby the forecast value is the same as the last observation's value. The naive forecast (random walk type) has commonly been introduced in the previous literature as a comparison with more advanced technical methods. Despite its simplicity, it has been shown to make better forecasts than several forecasting models (Atkeson and Ohanian, 2001). Overall, a comparison with the naive forecast is a basic comparison to prove the predictive power of the applied method. The other out-of-sample common comparable forecasting methods include ordinary least squares (OLS, expanding window), rolling OLS (fixed window), AR(1), and AR(2). More advanced methods have also been applied:

- Time-Varying Parameter (TVP) Model

The standard set-up for the TVP model is:

$$y_t = z_t\theta_t + \epsilon_t. \tag{10}$$

$$\theta_t = \theta_{t-1} + \eta_t. \tag{11}$$

where $\epsilon_t \sim N(0, H_t)$ and $\eta_t \sim N(0, Q_t)$. This can be considered a simple version of DMA when only one model, which contains all predictors, is to be estimated. The R-package used in this study, fDMA package, produces only in-sample forecasts for the TVP model, which always present smaller RMSEs than out-of-sample forecasts. Even though the comparison is biased in favor of TVP, DMA has better forecasts in almost all cases.

- Bayesian Vector Autoregression

Firstly, the reduced form of the VAR process is introduced:

$$\overrightarrow{Y}_t = \delta + \theta_1\overrightarrow{Y}_{t-1} + ... + \theta_p\overrightarrow{Y}_{t-p} + \overrightarrow{\epsilon}_t, \tag{12}$$
$$\overrightarrow{\epsilon}_t \sim N(0, \sum).$$

A conjugate normal-Wishart (δ, θ_1,..., θ_p, $\sum$) prior is used (e.g., Karlsson, 2013, Subsection 3.2.1). The prior is non-informative on δ (normal distribution, $\delta \sim N(\underline{\delta}, Var(\delta))$), and informative on $\sum$ (inverted Wishart), and on θ_1,..., θ_p (normal distribution). The prior mean for $\sum$ is diagonal, constructed with estimates of the variance obtained with OLS regressions. It is common to set priors as follows (e.g., Litterman, 1986):

$$\begin{gathered} E(\theta_1) = I,\, Var(\theta_1) \propto \pi_1^2 \qquad (13) \\ E(\theta_2) = 0,\, Var(\theta_2) \propto \frac{\pi_1^2}{(2^{\pi_3})^2} \\ E(\theta_3) = 0,\, Var(\theta_3) \propto \frac{\pi_1^2}{(3^{\pi_3})^2} \\ ... \\ E(\theta_p) = 0,\, Var(\theta_p) \propto \frac{\pi_1^2}{(p^{\pi_3})^2} \\ E(\delta) = \underline{\delta},\, Var(\delta) \propto (\pi_1\pi_4)^2 \end{gathered}$$

where $\propto$ denotes "proportional to", π_1 is the overall variance, π_3 is the lag decay, π_4 is the variance of the constant and deterministic components, and $\underline{\delta}$ is the prior mean of deterministic components, which is usually set to 0. Therefore, with π_1, π_3 and π_4 decided, BVAR can forecast all variables contained in $\overrightarrow{Y}_t$. For this study, $\pi_1 = 0.1$, $\pi_3 = 0.5$, and $\pi_4 = 1$, and the optimal lag is chosen based on the Bayesian information criterion. This study also runs BVAR in two cases, first, by using all the predictors (Large BVAR) and second, by using some predictors that are chosen from the good predictors of the DMA forecasting (Small BVAR).

4 Data

This section describes the data employed to produce the forecasts for inflation and economic growth rates of Vietnam for different forecasting horizons. The inflation rate for different forecasting horizons is calculated using the following formula:

$$\pi_{t,t+h} = \frac{1}{h} log(\frac{CPI_{t+h}}{CPI_t}), \qquad (14)$$

where CPI_t is the CPI at time t.

The economic growth rate for different forecasting horizons can be calculated using the following formula:

$$g_{t,t+h} = \frac{1}{h} log(\frac{IPI_{t+h}}{IPI_t}), \qquad (15)$$

where IPI_t is the industrial production index at time t.

Table 1: All Variables in Forecasting Model

Name	Definition	Period	Frequency	Source
INF	Inflation rate	1995-2019	Monthly	GSO
GROW	Growth rate of industrial production index	2008-2019	Monthly	GSO
M2	Growth rate of money aggregate M2	2000-2019	Quarterly in 2000, Monthly in 2001-2019	SBV
CRE	Growth rate of banking credit	2004-2019	Quarterly in 2004-2011, Monthly in 2012-2019	SBV
VNI	Growth rate of VN Index of Ho Chi Minh Stock Exchange market	2002-2019	Monthly	investing.com
OVN	Averaged overnight interest rate in Vietnam's interbank market	2004-2019	Monthly	SBV
SPREAD6	Spread between averaged overnight and 6-month rates in interbank market	2007-2019	Monthly	SBV
SPREAD9	Spread between averaged overnight and 9-month rates in interbank market	2012-2019	Monthly	SBV
FDI	Growth rate of disbursed foreign direct investment	1996-2019	Quarterly	SBV
OIL	Growth rate of oil price in global market	1995-2019	Monthly	WB
USIPI	Growth rate of IPI of the United States	1995-2019	Monthly	IFS
USCPI	Growth rate of CPI of the United States	1995-2019	Monthly	IFS

Note: GSO stands for General Statistics Office of Vietnam, SBV stands for State Bank of Vietnam, WB stands for World Bank, IFS stands for International Financial Statistics, which is a database of International Monetary Fund.

Table 2: Statistical Summary of Dependent Variables

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**	**ADF**
INF1	300	0.0051	0.0082	-0.0111	0.0384	-5.4181***
INF6	295	0.0049	0.0055	-0.0057	0.0295	-2.2692
INF12	289	0.0049	0.0044	-0.0022	0.0208	-3.1974*
GROW1	143	0.0090	0.0900	-0.2980	0.2837	-7.4514***
GROW6	138	0.0095	0.0179	-0.0383	0.0534	-8.97000***
GROW12	132	0.0093	0.0083	-0.0122	0.0359	-2.0094

Note: ADF means the statistics from the augmented Dickey-Fuller unit root tests. *, ** and *** denote rejections of non-stationarity at the 10%, 5% and 1% significance levels, respectively.

Table 1 describes the data and defines the variables used. The data were collected from January 1995 to December2019. Although most of the series are monthly, for some variables in some periods or the whole sample, only quarterly data are available. These data are for FDI for the whole sample, M2 for the year of 2000, and CRE for the period 2004–2011. For these variables, we use the most recent information at the time that the forecast was made. Further details are given later in this section.

From Table 1, among the variables, apart from two dependent variables (i.e.,INF and GROW), M2 and CRE are variables representing the impact of monetary policy on the forecast variables, while the group of VNI, OVN, SPREAD6, and SPREAD9 variables is included to estimate the impact of financial variables on forecast variables. Last but not least, to consider the possible impact of external variables on the Vietnamese macroeconomy, FDI, OIL, USIPI, and USCPI are also included. The statistical summary and unit root test results of the dependent variables and predictors are presented in Tables 2 and 3, respectively.

Tables 2 and 3 show the statistical summary and ADF test results of the dependent and independent variables employed in the forecasting model. All the time series of the independent variables are proved to be stationary by the ADF test, which means that all of these time-series can enter the model at their level without requiring any transformation. Regarding the stationarity of the dependent variables, the time series of INF1, INF12, GROW1, and GROW6 all prove to be stationary by the ADF test.

Table 3: Statistical Summary of Predictors

Variable	Obs.	Mean	Std. Dev.	Min	Max	ADF
M2	235	0.0180	0.0166	-0.0176	0.1153	-6.1418***
CRE	187	0.0183	0.0121	-0.0187	0.0449	-3.4962**
VNI	207	0.0119	0.0896	-0.2401	0.3852	-6.6632***
OVN	183	0.0556	0.0369	0.0047	0.1831	-3.4345*
SPREAD6	156	0.0110	0.0143	-0.0448	0.0507	-4.5644***
SPREAD9	86	0.0219	0.0136	-0.0006	0.0639	-3.4845**
FDI	283	0.0583	0.2091	-0.2605	0.8333	-6.3834***
OIL	300	0.0080	0.0816	-0.2706	0.2244	-7.0508***
USIPI	300	0.0015	0.0191	-0.0498	0.0563	-5.1119***
USCPI	300	0.0018	0.0034	-0.0192	0.0122	-8.5249***

Note: ADF means the statistics from the augmented Dickey-Fuller unit root tests. *, ** and *** denote rejections of non-stationarity at the 10%, 5% and 1% significance levels, respectively.

The time series of INF6 and GROW12 do not prove to be stationary by the ADF test, but they are all stationary by another test for stationarity, is the Kwiatkowski-Phillips-Schmidt-Shin test, known as the KPSS test. Therefore, the time series of the dependent variables also enter the model at their level without requiring any transformation.

Dealing with missing data and different frequencies

As DMA allows for the forecasting model to change over time, this property helps to deal with missing data. Specifically, we insert 0 for missing data, and the method does not give these 0 values forecasting power; therefore, the models with missing data are not used. However, when the data become available, the model containing that variable is more likely to be used, as DMA dynamically rotates among the models.

The frequency of the dependent variable y_t is monthly, but some predictors (i.e., FDI, M2, and CRE) are available only quarterly. These predictors are quarterly growth rates. To forecast y_t, we use the information that is already publicly available at time t for both quarterly and monthly variables, and include it in the vector z_t (equation (1)). It would be ideal to have monthly information for all variables, but it is better to use the quarterly data in some way, rather than not to use them at all. Given that the main purpose of the analysis is to obtain a good forecast, using all the available information could be important, even if the information is at a different frequency. To use the quarterly data, in period t, we define the value of the predictor z_t as the most recent value of quarterly data available at period $t-1$ (divided by 3 to make the quarterly growth rates comparable to other monthly growth rates). For example, FDI is quarterly data, and would enter z_t as follows:

t	z_t
January 1999	FDI in 1998 Q4
February 1999	FDI in 1998 Q4
March 1999	FDI in 1998 Q4
April 1999	FDI in 1999 Q1
May 1999	FDI in 1999 Q1
June 1999	FDI in 1999 Q1
July 1999	FDI in 1999Q2
...	...

Given that the main purpose of this study is to produce a good forecast and to utilize as much available information as possible, the same treatment is also applied to quarterly data of M2 and CRE.

5 Forecasting Results

In this section, the first two subsections present the forecasting results of the inflation rate and economic growth rate, respectively. The last subsection compares the forecasting performances of DMA, DMS, and other forecasting methods. For each forecasting exercise, the averaged number of predictors and posterior inclusion probabilities of good predictors are introduced. Regarding the computation of these numbers, the averaged number of predictors (or averaged size of the forecasting model) at each point in time is calculated as:

$$E(Size_t) = \sum_{k=1}^{K} \pi_{t|t-1,k} Size_{k,t}$$

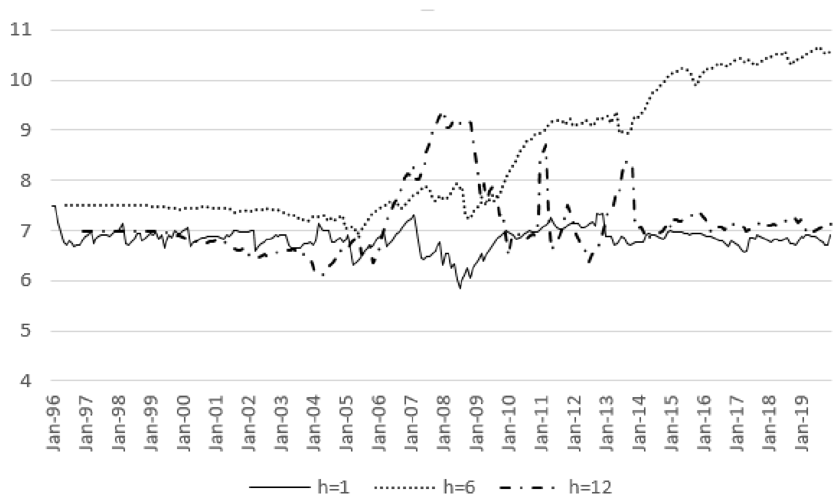

Figure 1: Averaged Number of Predictors for Inflation Rate Forecast

where $E(Size_t)$ is the averaged size of the forecasting model (or averaged number of predictors) at time t; $Size_{k,t}$ is the number of predictors in model k at time t; and $\pi_{t|t-1,k}$ is the probability that model k is the true model at time t given the information up to time $t-1$ (or the weight of model k at time t). The posterior inclusion probability of a predictor is the total weights of the models containing that particular predictor. As the models change over time, the posterior inclusion probability of a predictor also changes over time. Here, only the inclusion probabilities of good predictors are introduced; and a good predictor is defined as that whose inclusion probability is greater than 50% for at least at one point in time.

5.1 Inflation Rate Forecast

Figure 1 shows the averaged number of predictors for forecasting the inflation rate at different horizons. All three lines for 1 month (h = 1), 6 months (h = 6), and 1 year (h = 12) horizons move differently from each other. This shows not only that the forecasting model for each horizon changes over time, but also that the ways in which the models for different horizons change are different. Specifically, for h = 1, the averaged number of predictors frequently fluctuates between six and seven. For h = 6, the averaged number of predictors is stable at around seven before significantly increasing from 2007. For h = 12, the averaged number of predictors fluctuates between

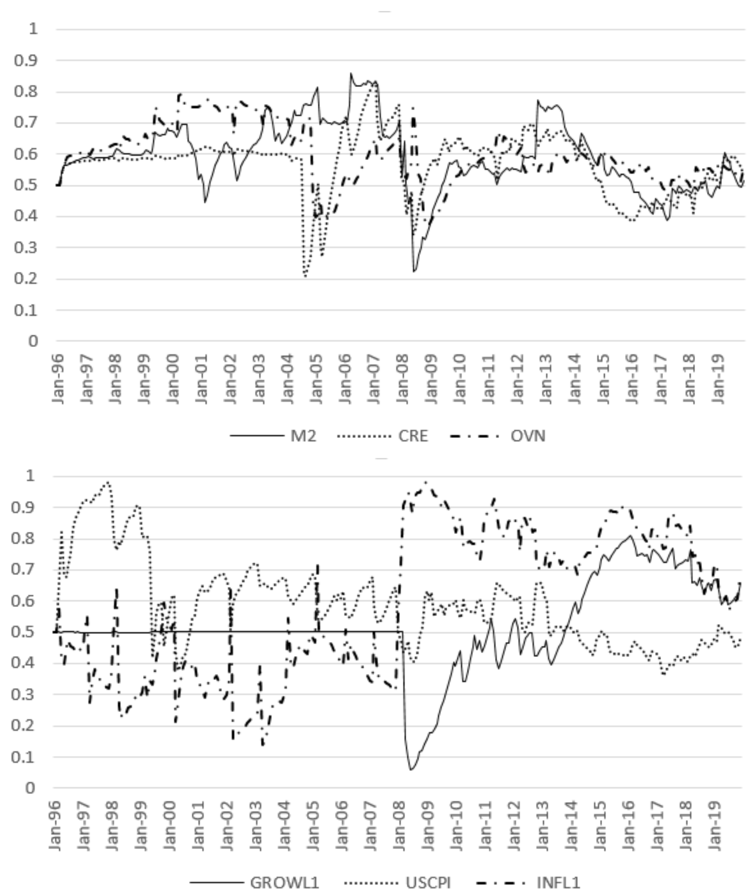

Figure 2: Posterior Inclusion Probabilities of Good Predictors (Inflation Rate, h = 1)

seven and nine in the period 2007–2011 before becoming stable at seven in recent years.

Figure 2 shows the posterior inclusion probabilities of good predictors for forecasting next month's inflation rate (h = 1). The good predictors include M2, CRE, and OVN, which are monetary policy transmission-related variables and other variables, including current economic growth rate (GROWL1), current inflation rate (INFL1), and US inflation rate (USCPI). From the top graph, M2, CRE, and OVN display inclusion probabilities of approximately 50% in recent years, although in the past, their inclusion probabilities were much higher. This result is reasonable, as any change in monetary policy needs time to affect the market, particularly the inflation rate. However, in the past, when the inflation rate of Vietnam was very volatile, even an announcement of a change of monetary policy from the SBV could instantly affect the market, and therefore, the inclusion probabilities of these variables were quite high at some points in the past.

From the bottom graph of Figure 2, the current inflation rate (INFL1) and economic growth rate (GROWL1) of Vietnam show significantly higher inclusion probabilities than USCPI from 2013. This shows that in a time of stability for both the domestic economy and the global economy, the future inflation rate of Vietnam seems to be influenced more by the domestic economy's variables than by the global economy's variables. However, when there is a shock in the global economy, like the global financial crisis in 2008, USCPI displayed a high inclusion probability, which shows that the future inflation rate of Vietnam is sensitive to changes in the global economy.

Figure 3 shows the good predictors for forecasting the inflation rate of the next 6 months (h = 6). There are more identified good predictors for 6-month horizon forecasting than for 1-month horizon forecasting, which is consistent with the previous result that the averaged number of predictors for h = 6 is significantly higher than those numbers for h = 1. The top graph shows that in forecasting the inflation rate for the 6-month horizon, the current economic growth rate (GROWL1) has less predictive power than the current inflation rate (INFL1) and the inflation rate of the previous year's same month (INFL12). Together with INFL1 and INFL12, M2 also shows some predictive power for the future inflation rate in the next 6 months. The central graph shows the increasing predictive power of CRE and financial variables, including SPREAD6, VNI, and OVN. In particular, from 2013, the inclusion probability of CRE is frequently higher than 80%, which implies a high predictive power of banking credit for the future inflation rate of Vietnam. The bottom graph shows the increasing inclusion probabilities of external variables, including FDI, OIL, USIPI, and USCPI, which suggests that the future inflation rate of Vietnam for a longer horizon, like 6 months, seems to be affected more by the movements of external variables than a shorter horizon is.

Figure 4 shows inclusion probabilities of good predictors for forecasting the inflation rate of the next year (12-month horizon). The top graph shows the inclusion proba-

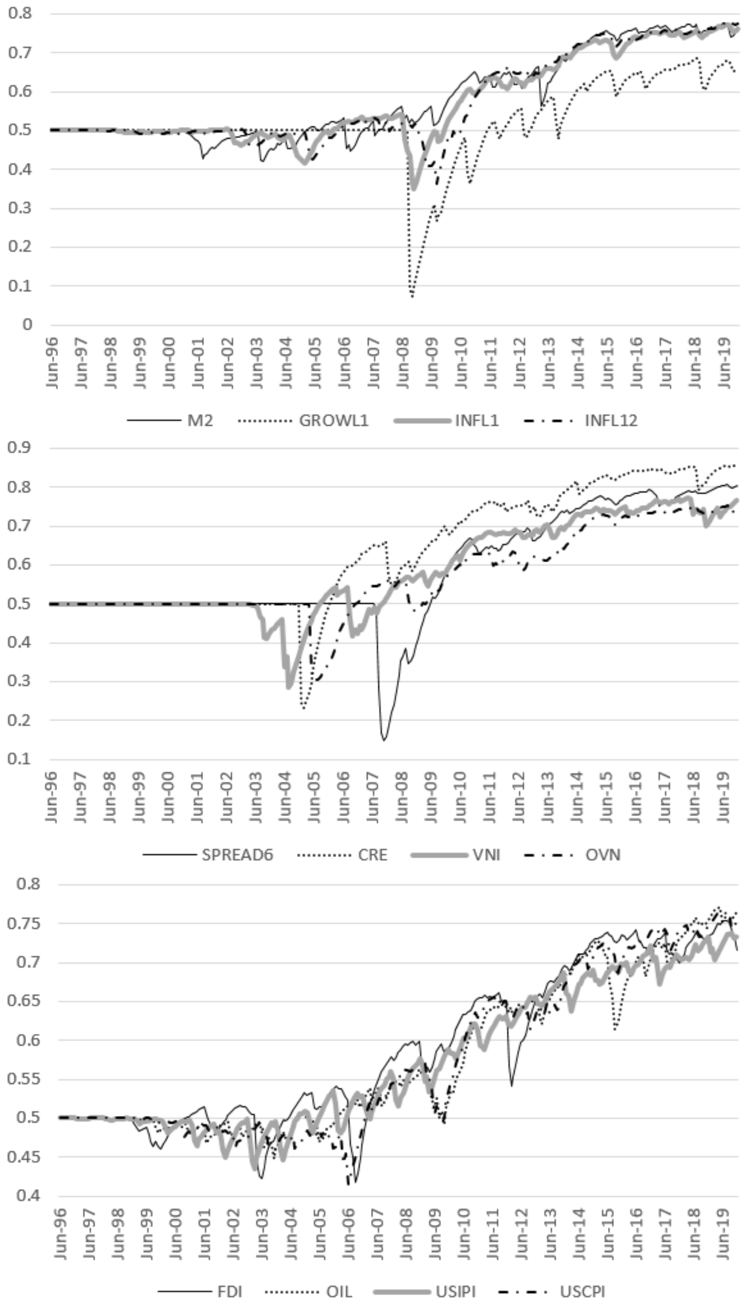

Figure 3: Posterior Inclusion Probabilities of Good Predictors (Inflation Rate, h = 6)

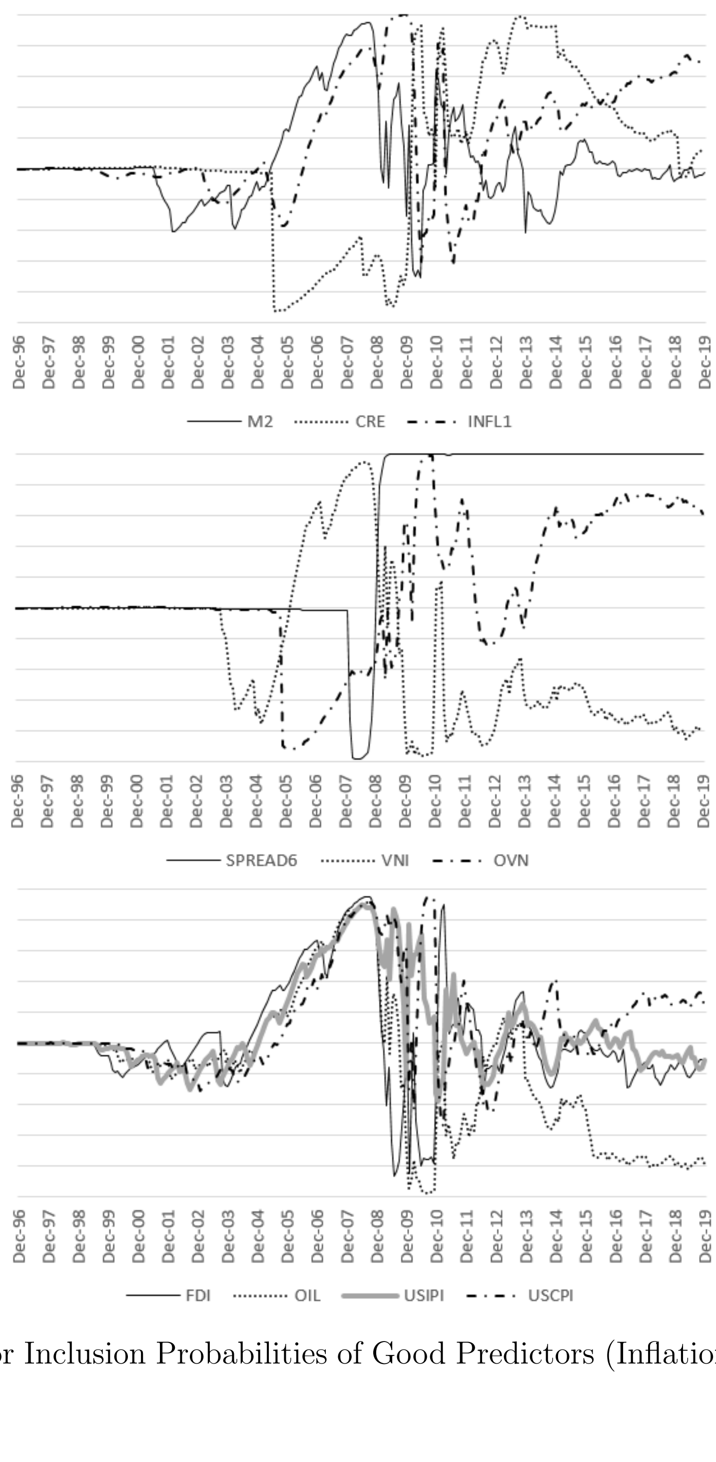

Figure 4: Posterior Inclusion Probabilities of Good Predictors (Inflation Rate, h = 12)

bilities of monetary policy transmission-related variables, including M2 and CRE, and the current 12-month inflation rate (INFL1). Among these predictors, INFL1 shows an increasing and higher inclusion probability than M2 and CRE in recent years. In fact, since 2013, the inflation rate of Vietnam has been stable and frequently less than 5% per year; therefore, the current inflation rate is believed to have high predictive power for the future inflation rate of Vietnam. The central graph shows the inclusion probabilities of financial variables, including SPREAD6, VNI, and OVN. The inclusion probabilities of SPREAD6 and OVN are significantly higher than that of VNI, showing that money market variables, like SPREAD6 and OVN, have higher predictive power for the next year's inflation rate of Vietnam than a stock market variable, like VNI. This finding is consistent with the fact that financial intermediaries are playing a more important role than the stock market in stimulating capital for economic activities in Vietnam. In addition, the bottom graph shows that, similar to the case of h = 6, external variables display some predictive power for the future inflation rate of Vietnam in the next 12 months.

Table 4: Coefficient Means for Inflation Rate Forecast

	INFL1	GROWL1	M2	CRE	SPREAD6	OVN
h = 1	0.3336	0.0003	0.0347	0.0190	-0.0016	0.0101
h = 6	-0.0084	0.0002	0.0201	0.0520	0.0264	0.0111
h = 12	-0.1159	0.0001	0.0043	0.0233	0.0290	0.0094

	VNI	FDI	OIL	USIPI	USCPI
h = 1	0.0015	-0.0011	0.0000	-0.0326	0.5150
h = 6	-0.0019	-0.0015	0.0043	-0.0016	-0.0224
h = 12	-0.0001	-0.0003	0.0006	0.0014	0.0107

Table 4 presents the coefficient means of frequently identified good predictors for forecasting the inflation rate for different horizons. The coefficient mean of the current inflation rate (INFL1) generally has the highest magnitude throughout different horizons. According to Table 4, while the current month's inflation rate has a positive impact on the next month's inflation rate, the current 6-month inflation rate has a negative impact on the inflation rate of the next 6 months. This empirical result can be interpreted as follows: a high inflation rate in the last 6 months tends to result in a lower inflation rate in the next 6 months. The same logic can be applied to explain the negative coefficient mean of INFL1 in h = 12, which means that if the economy has experienced a high inflation rate in the last 12 months, in the next 12 months, the inflation rate is likely to be lower than in the previous period.

Figure 5 shows the predicted values of the inflation rate beyond the sample span and their 95% credible intervals. Given that the sample span used in this study is from January 1995 to December2019, the top graph of Figure 5 predicts the monthly inflation rate in January2020, the center graph predicts the averaged 6-month inflation rate from January 2020 to June2020, and the bottom graph predicts the averaged 12-month inflation rate from January 2020 to December 2020. In fact, the monthly inflation rate of January 2020 is 1.23% and the averaged 6-month inflation rate from January 2020 to June 2020 is -0.1%, which are both inside the corresponding 95% credible intervals; this is evidence of the suitability of DMA for forecasting the inflation rate of Vietnam.

5.2 Economic Growth Rate Forecast

Figure 6 shows the averaged numbers of predictors for forecasting the economic growth rate for different horizons. The averaged numbers of predictors for forecasting the future economic growth rate at different horizons fluctuate over time and the way that these numbers fluctuate also differs from each other. Similar to the exercise for forecasting the inflation rate, this evidence suggests that the forecasting model for the economic growth rate of Vietnam is changing over time. Specifically, the averaged number of predictors for the 1-month horizon remains stable at six from 2015. However, the number for the 6-month horizon fluctuates around four for most of the sample. Finally, among different horizons, the averaged number of predictors for the 12-month forecasting horizon fluctuates the most, from lower than two to seven; recently this number has remained stable at around five.

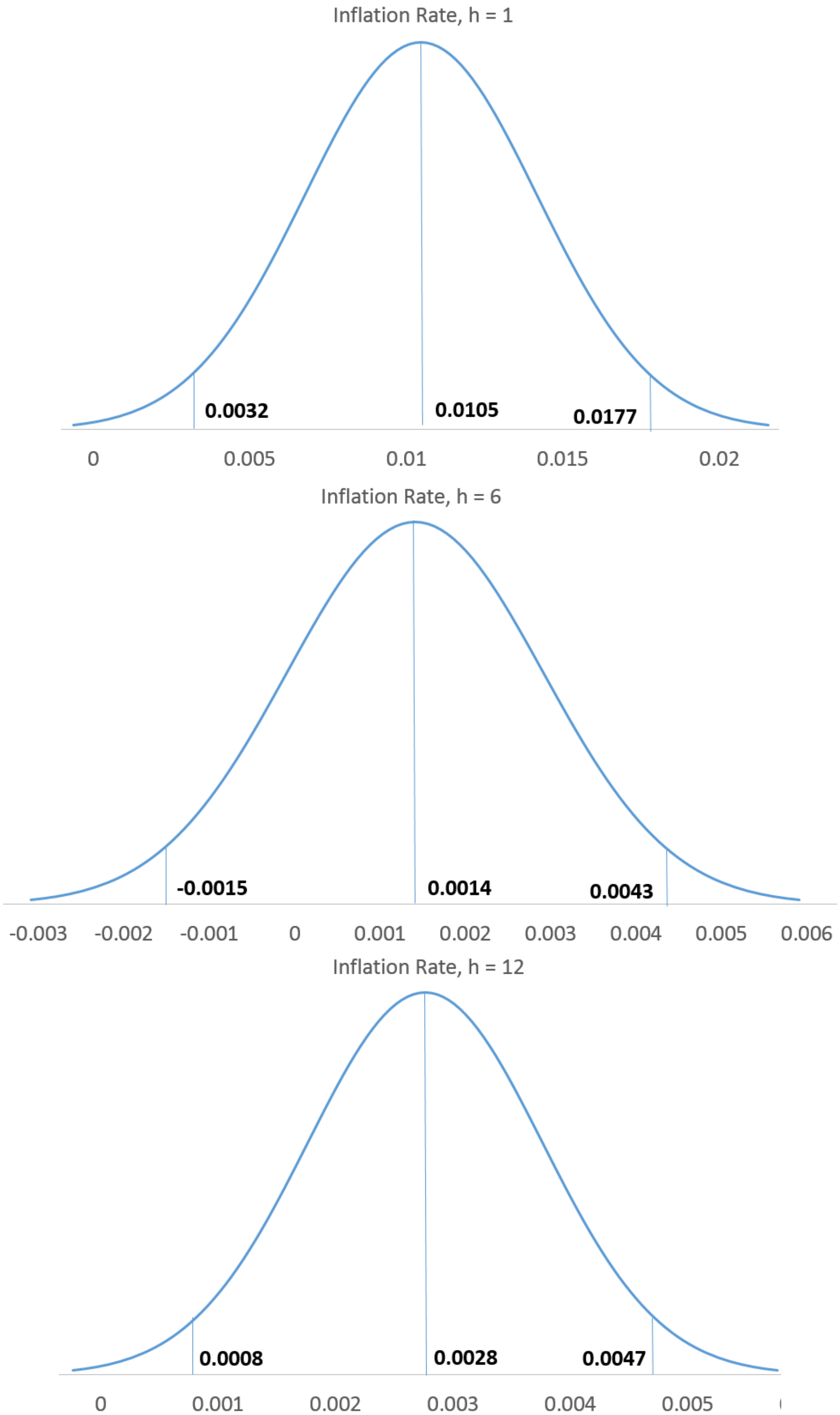

Figure 5: Predicted Values Beyond Sample Span and 95% Credible Intervals (Inflation Rate)

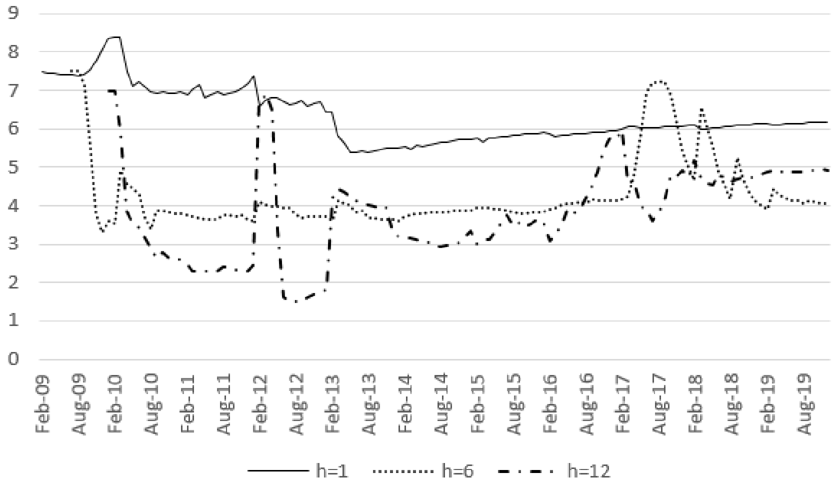

Figure 6: Averaged Number of Predictors for Economic Growth Rate Forecast

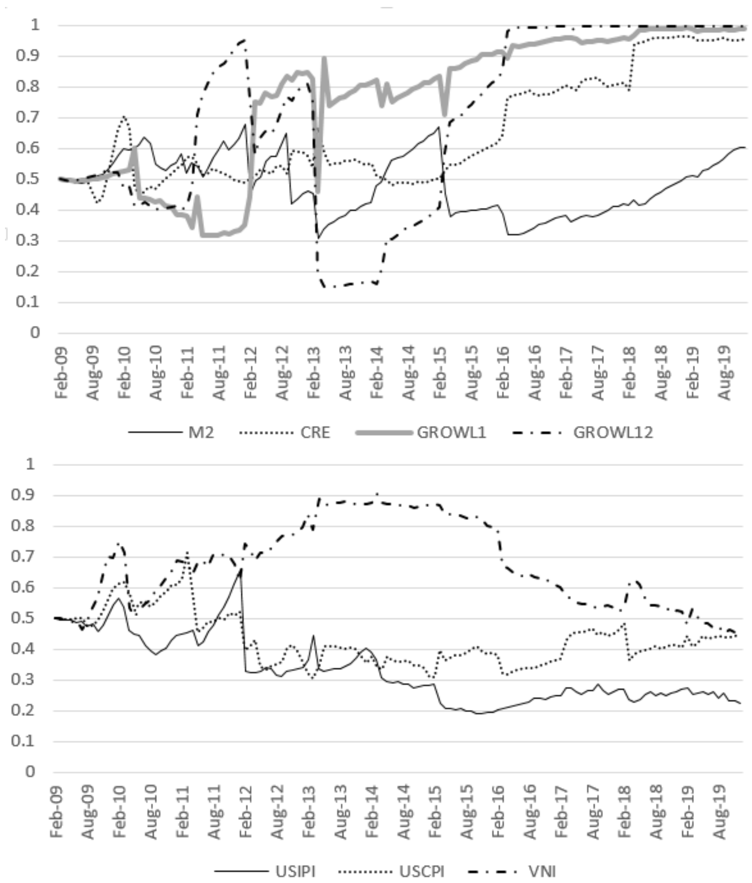

Figure 7: Posterior Inclusion Probabilities of Good Predictors (Economic Growth Rate, h = 1)

From Figure 7, there are seven explanatory variables considered to be good predictors in forecasting next month's economic growth. They are the current economic growth rate (GROWL1), the economic growth rate of same month last year (GROWL12), M2, CRE, USIPI, USCPI, and VNI. The variables related to monetary policy transmission, M2 and CRE, were found to be good predictors, which suggests that a change in monetary policy might have an instant impact on the market participants' expectations, leading to some change in the economic growth rate in the short term. However, the inclusion probabilities of monetary policy-related variables are not as high as those of lagged values of economic growth rate, and both GROWL1 and GROWL12 display very high predictive power for the future economic growth rate of the next month (refer to the top graph of Figure 7). From the bottom graph, VNI, USIPI, and USCPI display lower predictive power for the next month's economic growth rate of Vietnam, as their inclusion probabilities are significantly lower than those of monetary policy-related predictors, like M2 and CRE, and lagged values of economic growth rate, like GROWL1 and GROWL12.

Figure 8 shows good predictors identified for forecasting the economic growth rate at h = 6. The identified good predictors for 1-month horizon (Figure 7) are quite different from those for 6-month horizon (Figure 8). Specifically, from the top graph, VNI, current economic growth rate (GROWL1), and lagged economic growth rate of the same month last year (GROWL12) display high predictive power for the economic growth rate in the next 6 months. Meanwhile, the bottom graph shows the inclusion probabilities of the money market variable SPREAD9 and the external variables FDI and OIL. Figure 8 also shows that GROWL1 and GROWL12 generally have higher inclusion probabilities than the other variables.

We now move to forecast the economic growth rate at h = 12 (see Figure 9). The identified good predictors are current economic growth rate (GROWL1), current inflation rate (INFL1), USCPI, and financial variables, including SPREAD6, SPREAD9, and VNI. From the top graph, the current economic status, INFL1 and GROWL1, have high predictive power for the future economic growth rate, especially GROWL1.

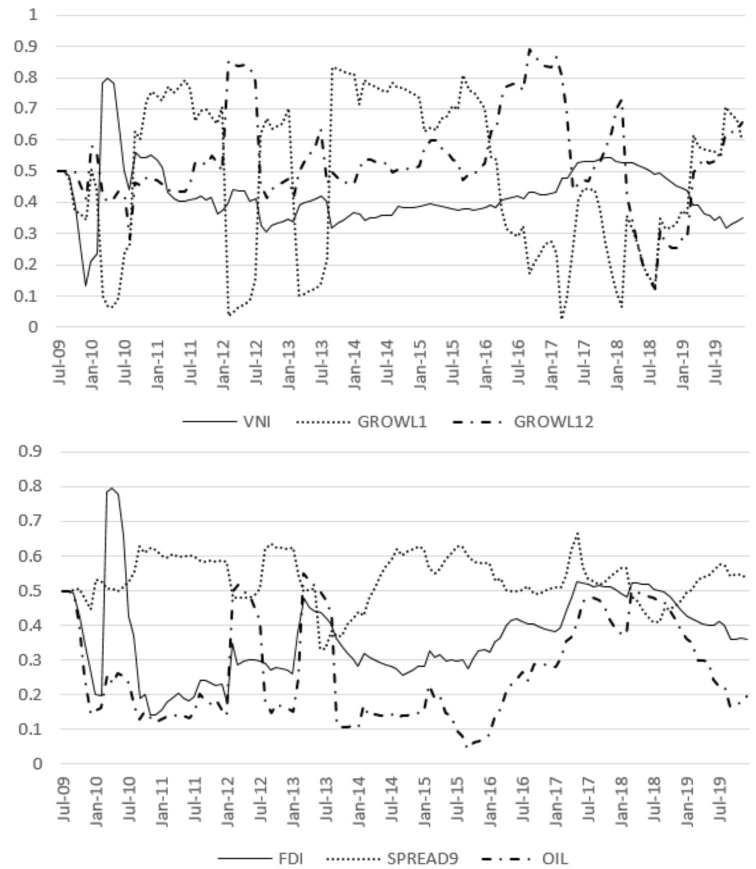

Figure 8: Posterior Inclusion Probabilities of Good Predictors (Economic Growth Rate, h = 6)

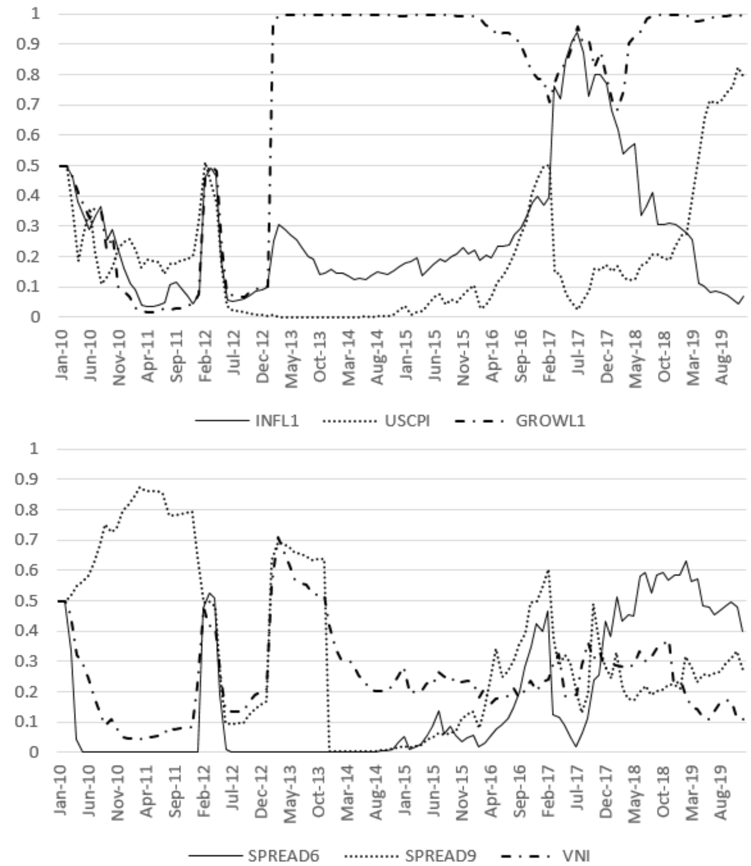

Figure 9: Posterior Inclusion Probabilities of Good Predictors (Economic Growth Rate, h = 12)

This shows that there is strong correlation between the economic growth rates of different years in Vietnam, which is consistent with the fact that the Vietnamese economic growth rate tends to be stable around 5% to 6% throughout the sample years. From the bottom graph, money market variables, including SPREAD6 and SPREAD9, generally display higher inclusion probabilities than VNI, which represents for the movement of stock market. This empirical result confirms that among financial variables, the predictive power of money market variables for future economic growth rate of Vietnam for long horizons, like 12 months, is higher than that of stock market variables.

Table 5: Coefficient Means for Economic Growth Rate Forecast

	GROWL1	GROWL12	INFL1	M2	CRE	SPREAD6
h = 1	-0.2486	0.3311	-	-0.1033	0.8815	-
h = 6	-0.3286	0.2029	-	-	-	-
h = 12	-0.1748	-	0.1725	-	-	0.0256

	SPREAD9	VNI	FDI	OIL	USIPI	USCPI
h = 1	-	-0.0946	-	-	-0.2446	0.2239
h = 6	0.0259	-0.0078	-0.0108	-0.0088	-	-
h = 12	-0.0078	-0.0005	-	-	-	-0.0339

Table 5 presents the coefficient means of good predictors for forecasting economic growth rate at different horizons. First, the good predictors for different horizons differ from each other[3]. Moreover, there are fewer predictors identified as good predictors for forecasting the economic growth rate than for forecasting the inflation rate. This suggests that forecasting the economic growth rate of Vietnam utilizes less information than forecasting the inflation rate, which may lead to lower accuracy in forecasting the economic growth rate (the next section shows the performances of different forecasting methods for forecasting the inflation and economic growth rates of Vietnam and provides some evidence).

Although most of the variables are identified as good predictors for only one horizon, current and past values of economic growth consistently show high predictive

[3]Only the coefficient means of good predictors appear in the table, and therefore, for some horizons, the coefficient means for some variables are not indicated.

power for the future economic growth rate at different horizons. Specifically, current economic growth rate (GROWL1) generally displays the strongest impact on future economic growth rate as its coefficient means are frequently the greatest in absolute value throughout horizons, among all variables. The negative signs of these coefficient means are consistent with the fact that the economic growth rate measured by the industrial production index display considerably high variance, leading the current economic growth rate may have negative impact on future economic growth rate. Meanwhile, the past value of economic growth rate in the same month last year has a positive impact on the future economic growth rate. This empirical result implies the seasonality of the economic growth rate of Vietnam.

Figure 10 shows the predicted values of the economic growth rate beyond the sample span and their 95% credible intervals. Specifically, the top graph of Figure 10 predicts the monthly economic growth rate in January 2020 and the centered graph predicts the averaged 6-month economic growth from January 2020 to June 2020, while the bottom graph predicts the averaged 12-month economic growth from January 2020 to December 2020. The economic growth rate measured by the industrial production index in January 2020 is reported as -0.1634, which is outside the 95% credible interval for January 2020. However, this result mainly comes from the fact that in 2020, Vietnam's longest holiday of the lunar new year, which usually occurs in February, unusually took place at the end of January; this led to the unusual drop of the industrial production index in January 2020. Therefore the realized rate in January is smaller than the lower bound of the credible interval. Meanwhile, the averaged 6-month economic growth rate in June 2020 is reported as -0.85%, which is comfortably inside the credible intervals computed by DMA; this illustrates the suitability of DMA for forecasting the future economic growth rate of Vietnam.

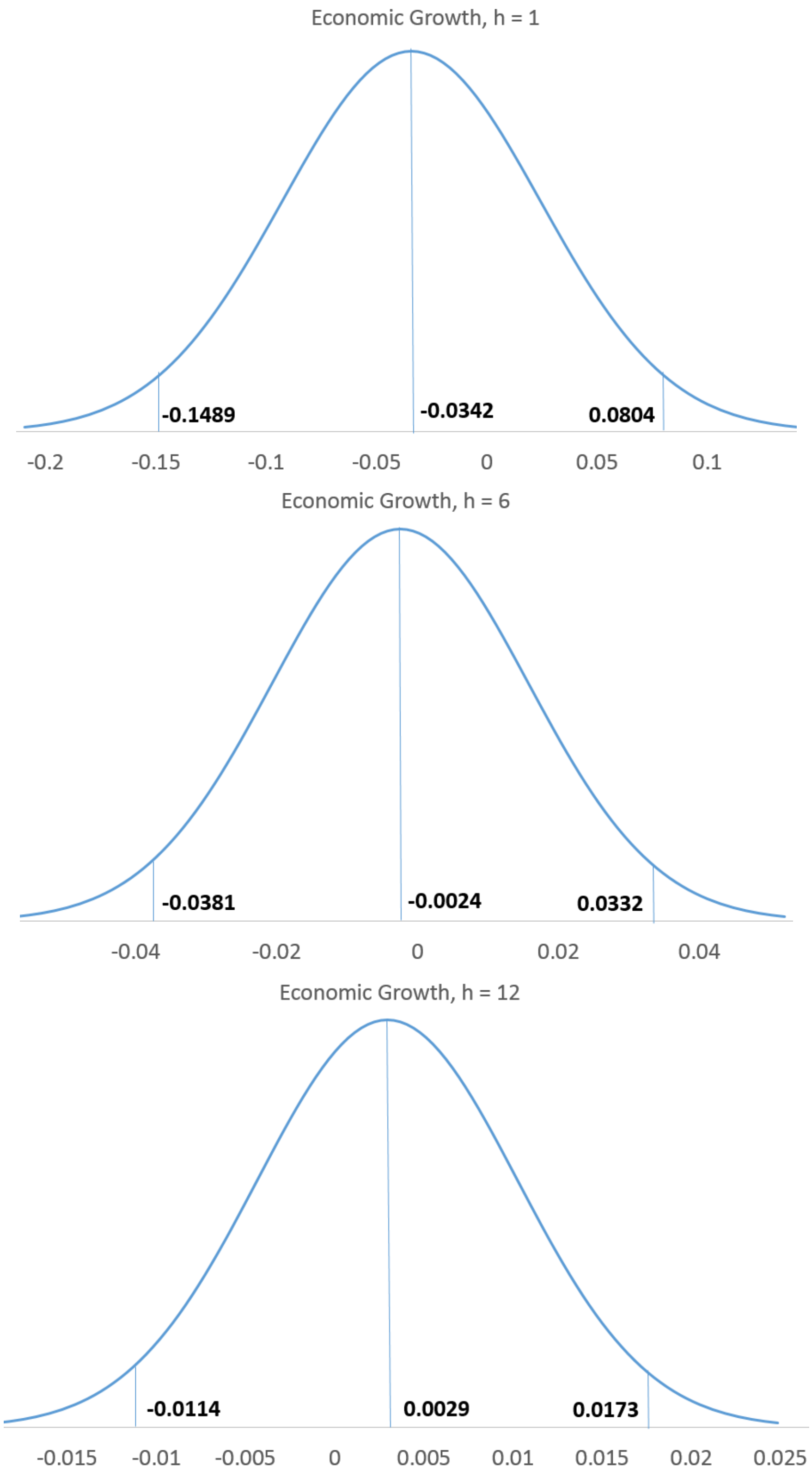

Figure 10: Predicted Values Beyond Sample Span and 95% Credible Intervals (Economic Growth Rate)

5.3 Compare DMA with other forecasting methods

This subsection compares the forecasting performance of DMA and DMS with the forecasting methods presented in Subsection 3.2, based on two criteria, namely, RMSE and mean absolute error (MAE).

Table 6: Comparing Different Methods in Inflation Rate Forecast

	h=1		h=6		h=12	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
DMA	0.0037	0.0028	0.0015	0.0012	0.0010	0.0008
DMS	0.0037	0.0031	0.0015	0.0012	0.0009	0.0007
Naive	0.0040	0.0032	0.0023	0.0019	0.0016	0.0013
AR(1)	0.0036	0.0027	0.0023	0.0019	0.0020	0.0018
AR(2)	0.0036	0.0028	0.0021	0.0016	0.0019	0.0017
OLS	0.0039	0.0030	0.0028	0.0023	0.0026	0.0021
Rolling OLS	0.0037	0.0029	0.0021	0.0016	0.0020	0.0014
TVP	0.0068	0.0048	0.0046	0.0034	0.0036	0.0028
Small BVAR	0.0045	-	0.0021	-	0.0016	-
Large BVAR	0.0050	-	0.0031	-	0.0026	-

Table 7: Comparing Different Methods in Economic Growth Forecast

	h=1		h=6		h=12	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
DMA	0.0585	0.0401	0.0182	0.0134	0.0073	0.0046
DMS	0.0578	0.0395	0.0175	0.0125	0.0077	0.0047
Naive	0.1452	0.0876	0.0338	0.0264	0.0158	0.0126
AR(1)	0.0823	0.0506	0.0210	0.0162	0.0124	0.0096
AR(2)	0.0812	0.0529	0.0195	0.0150	0.0128	0.0107
OLS	0.0599	0.0420	0.0197	0.0151	0.0118	0.0091
Rolling OLS	0.0585	0.0426	0.0198	0.0150	0.0120	0.0098
TVP	0.1263	0.0769	0.0167	0.0121	0.0084	0.0062
Small BVAR	0.0841	-	0.0239	-	0.0159	-
Large BVAR	0.0856	-	0.0229	-	0.0158	-

Tables 6 and 7 compare the forecasting performances of DMA, DMS, and other forecasting methods through forecasting exercises of inflation and economic growth rates, respectively, at different horizons. The RMSE and MAE of DMA and DMS in every forecasting exercise approximate each other; moreover, the RMSE and MAE of DMA and DMS are smaller than or approximate those of other forecasting methods in all forecasting exercises. This evidence shows that in forecasting the future inflation rate and economic growth rates of Vietnam, DMA and DMS can produce more accurate forecasts than other forecasting methods.

DMA is the best method for forecasting both Vietnamese inflation and economic growth, although it is better at forecasting inflation. Specifically, from Tables 6 and 7, comparing the inflation rate forecast and the economic growth forecast, the RMSE of the latter is significantly bigger than that of the former. This result indicates that forecasting the economic growth rate in Vietnam is more challenging than forecasting the inflation rate. This finding is consistent with the finding in the previous sub-section that less good predictors are identified in forecasting economic growth rate, which implies that less information can be utilized for forecasting this macroeconomic variable than for forecasting the inflation rate.

6 Conclusions

It is unquestionable that the macroeconomic variables of developing countries experience more structural breaks than do those of advanced countries. Therefore, one of the desirable methods for forecasting the macroeconomic variables of developing countries is DMA. This study applied DMA to forecasting the inflation and economic growth rates of Vietnam and yields the following conclusions.

This study provides evidence on the suitability of DMA for forecasting the macroeconomic variables of Vietnam and developing countries in general. First, from the DMA estimations, both the averaged number of predictors and the identification of good predictors change over time. This shows that a method allowing for model change, such as DMA, should be applied. Second, DMA was proved to be the best model among the forecasting methods for producing smaller RMSE or approximated the RMSEs of the other forecasting methods in all forecasting exercises. Finally, DMA computed the forecast values beyond the sample span and their 95% credible intervals. The realized values are generally inside the computed 95% credible interval of DMA, which shows its suitability for forecasting the future inflation and economic growth rates of Vietnam. Overall, DMA is expected to produce accurate forecasts for macroeconomic variables of developing countries.

Regarding the forecasting of inflation and economic growth for Vietnam, some good predictors were noticed, depending on the forecast variable and horizon, including variables related to monetary policy transmission (M2 and CRE), financial variables (SPREAD6 and OVN), and external variables. Specifically, the SBV's monetary policy was shown to have more predictive power for the future inflation rate than for the economic growth rate, which somehow shows the effectiveness of monetary policy in controlling inflation in Vietnam. Moreover, the predictive power of external variables, including OIL and FDI, are increasing. This brings both benefits and challenges for policy implementation. The advantage is that there is more information to be referred to for forecasting the future inflation and economic growth rates. However, the higher predictive power also signals a bigger impact of those external variables on domestic variables, which implies that the Vietnamese economy is becoming more sensitive to external shocks.

Given the increasing predictive power of external variables for the future macroeconomic condition of Vietnam, future research should develop a forecasting model with more informative external variables, which would enable researchers and policymakers to forecast the future macroeconomic condition of Vietnam more accurately. Particularly for variables representing the macroeconomic condition in the Vietnamese economy, instead of the standard US macroeconomic variables used, a forecasting model with Chinese macroeconomic variables should be considered, given that China is one of the biggest trading partners of Vietnam.

References

[1] Atkeson, A. and Ohanian, L., 2001, *Are Phillips Curves Useful for Forecasting Inflation?*, Federal Reserve Bank of Minneapolis Quarterly Review 25, 2-11.

[2] Bernanke, B.S. and Gertler, M., 1995, *Inside the Black Box: The Credit Channel of Monetary Policy Transmission*, Journal of Economic Perspectives 9(4), 27-48.

[3] Clarida, R., Gali, J. and Gertler, M., 2000, *Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory*, Quarterly Journal of Economics 115 (February), pp. 147-80.

[4] Cogley, T., Morozov, S. and Sargent, T., 2005, *Bayesian Fan Charts for U.K. inflation: Forecasting and Sources of Uncertainty in an Evolving Monetary System*, Journal of Economic Dynamics and Control 29, pp. 1893-1925.

[5] Filippo, G., *Dynamic Model Averaging and CPI Inflation Forecasts: A Comparison between the Euro Area and the United States*, Journal of Forecasting 34, 619-648.

[6] Groen, J., Paap, R. and Ravazzolo, F., 2009, *Real-time Inflation Forecasting in a Changing World*, Econometric Institute Report, 2009-19, Erasmus University Rotterdam.

[7] Karlsson, S., 2013, *Chapter 15 - Forecasting with Bayeasian Vector Autoregression*, Handbook of Economic Forecasting, Vol.2, Part B, 791-897.

[8] Koop, G., and Korobilis, D., 2012, *Forecasting inflation using dynamic model averaging*, International Economic Review 53, 867-886.

[9] Litterman, R.B., 1986, *Forecasting with bayesian vector autoregressions - five years of experience*, Journal of Business and Economic Statistics 4, 25?38.

[10] Nguyen Nhu Ty and Tran Thanh Tuyen, 2015, *Mathematical Development and Evaluation of Forecasting Models for Accuracy of Inflation in Developing Countries: A Case of Vietnam*, Discrete Dynamics in Nature and Society Volume 2015, Article ID 858157, available at http://dx.doi.org/10.1155/2015/858157.

[11] Nicoletti, G. and Passaro, R., 2012, *Sometimes it helps: The evolving predictive power of spreads on GDP dynamics*, ECB Working Paper No. 1447.

[12] Raftery, A., Karny, M. and Ettler, P., 2010, *Online Prediction Under Model Uncertainty via Dynamic Model Averaging: Application to a Cold Rolling Mill*, Technometrics 52-1, pp. 52-66, DOI: 10.1198/TECH.2009.08104.

[13] Stock, J. and Watson, M., 1999, *Forecasting Inflation*, Journal of Monetary Economics 44, 293-335.

[14] Tran Thanh Hoa, 2007, *Forecasting In ation in Vietnam with Univariate and Vector Autoregressive Models*, Graduate Institute of International and Development Studies (IHEID)'s Working Paper No. HEIDWP05-2017.