University of Pretoria
Department of Economics Working Paper Series

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Working Paper: 2025-23
July 2025

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Forecasting GDP with Oil Price Shocks: A Mixed-Frequency Time-Varying Perspective

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Abstract

This paper investigates the predictability of supply and demand oil price shocks on U.S. Gross Domestic Product (GDP) using several Mixed Data Sampling (MIDAS) models that link quarterly GDP to monthly oil price shocks for the period 1981-2023. The main findings reveal that oil demand shocks – particularly economic activity and inventory shocks- have higher forecast ability than oil supply shocks, highlighting the importance of disentangling oil price shocks into their underlying components. Additionally, our results suggest that the Time Varying Parameter (TVP)-MIDAS model most effectively captures the dynamic relationship between oil price fluctuations and economic activity, pointing to the heterogeneous impact of oil price shocks over time. Finally, when we extend our analysis to other regions in the world, the results suggest that while oil demand shocks play a significant role in forecasting economic activity in advanced regions, the emerging regions are more vulnerable to oil supply shocks.

Keywords: Oil price shocks, economic activity, Mixed-Data-Sampling (MIDAS), Time-Varying Parameter MIDAS (TVP-MIDAS), Forecast evaluation.

JEL Classification: C22, C53, Q41.

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1. Introduction

In his seminal paper, Hamilton (1983) established a significant relationship between oil price shocks and US economic activity, empirically showing that seven out of eight US recessions since World War II were preceded by increases in oil prices. Since then, a vast body of literature has examined the relationship between oil price fluctuations and U.S. Gross Domestic Product (GDP), exploring the transmission mechanisms and economic implications of these shocks (Hamilton, 1996, 2003; Rotemberg and Woodford, 1996; Barsky and Kilian, 2001; Kilian, 2008, 2009; Baumeister and Peersman, 2013; Herrera et al., 2019). However, despite the well-documented relationship between oil prices and economic activity, empirical evidence suggests that the nature and magnitude of this relationship depend on various factors. First of all, the academic literature suggests that this relationship will vary depending on the underlying source of oil price fluctuations —specifically, whether they are driven by supply or demand shocks—underscoring the necessity of differentiating between these types of shocks (Kilian, 2009; Kilian and Park, 2009; Ready, 2018; Herrera et al., 2019; Baumeister and Hamilton, 2019). Baumeister and Hamilton (2019), for example, propose decomposing oil price changes into components driven by supply and demand. In this context, while oil supply shocks can be attributed to shortfalls in oil production, oil demand shocks are typically related to expansions in the global economy. Demand-side shocks include economic activity, oil consumption demand and oil inventory demand shocks. The economic activity shock, also known as aggregate demand shock, measures shifts in global real economic activity, which affects global oil demand and dominates instant price changes. An oil consumption demand shock will increase production and price simultaneously, but the increased oil price brought by this shock will never affect the economic activity. Kilian and Murphy (2014) also consider oil inventory demand shocks, explaining that a positive storage (or speculative) demand shock increases oil production and inventories but decreases real economic activity. Thus, the analysis of the predictability of each of these shocks on economic activity will shed light on which are the main mechanisms that drive the impact of oil price shocks on GDP. Moreover, the academic literature has reported evidence that the dynamic effects of oil shocks on the US economy have changed over time (Baumeister and Peersman, 2013; Pan et al., 2018; Kilian and Vigfusson, 2017), suggesting a decrease in the economy's sensitivity to oil market shocks. In fact, studies that explored the oil price-economic activity relationship after the 1986 oil price collapse found evidence of instability in this relationship (Herrera et al., 2019). Based on these findings, a line of research has emerged investigating the allowing for time-varying effects of oil price fluctuations (Baumeister and Peersman, 2013; Kilian and Vigfusson, 2017). Additionally, oil price changes also exert different impacts on economic activity depending on an economy's oil dependence. For oil-exporting countries, higher prices generally lead to increased revenues and GDP growth, while for oil-importing countries, rising prices tend to increase costs and slow economic growth (Hamilton, 1983; Polat et al., 2025). Additionally, while the academic literature finds strong evidence of in-sample predictability of oil price shocks for economic activity Hamilton, 2003, 2011; Kilian and Vigfusson, 2013), the out-of-sample ability of oil price shocks to predict economic activity remains unclear (Bachmeier, Li, and Liu, 2008; Ravazzolo and Rothman, 2013, 2016; Pan et al., 2018) since it heavily depends on the definition of the oil price shock, the choice of the models or the time horizon of the predictability, among others.

In this context, the objective of this paper is to examine the ability of (supply and demand) oil price shocks to predict US (and global) GDP at different time horizons using several Mixed Data Sampling (MIDAS) models which relate quarterly GDP with monthly oil price shocks for the period 1981-2023. The main contributions of the paper are the following. First, we decompose oil price innovations into supply and demand (oil consumption, inventory and economic activity) shocks following the approach of Baumeister and Hamilton (2019) and analyse their forecasting activity for US GDP using data from 1981 to 2023, a period which includes different episodes of oil price movements, the Global Financial Crisis or the COVID pandemic. While previous studies demonstrated the feasibility on nowcasting GDP levels, most of them have not analyse the impact of oil price fluctuation in a decomposed perspective (Chan et al., 2024; Hassani et al., 2019; Jardet and Meunier, 2022; Kuzin et al., 2011). Second, since GDP is announced quarterly, while oil shocks and most macroeconomic variables closely related to GDP (e.g., CPI, policy rate, etc.) are announced monthly, we use various Mixed-Data Sampling (MIDAS) models to evaluate the forecasting ability of oil price shocks. Initially proposed by Ghysels (2004), MIDAS has become a popular choice for econometrical forecasting in recent years for its ability to integrate macroeconomic variables with different data frequencies by specific weighting scheme. Third, in order to account for the non-linear and time-varying relationship between oil prices and US economic activity, we examine whether time-varying parameter MIDAS (TVP-MIDAS) models outperform standard MIDAS models. The earliest constant coefficient MIDAS, also known as standard MIDAS (std-MIDAS) assumed a fixed predict coefficient. However, Guérin and Marcellino (2013) pointed out that the prediction relationship between high frequency and low frequency data may change over time, which a fixed parameter is unable to catch. They introduced the Markov-switching MIDAS (MS-MIDAS), which considers flexible predictors coefficient under different market regimes (e.g. expansions and recessions). Another prevalent model is the TVP-MIDAS model, in which the predictor coefficients are function of time. It allows smooth and continuous changes in coefficients over time rather than discrete regime shifts, which is more robust to time variation in macroeconomic relationships (Pan et al., 2018; Schumacher, 2014; Chan et al., 2024; Safi et al, 2024; Lu et al, 2024). A TVP-MIDAS model is an ideal choice for examining the relationship between US GDP and oil shocks, although related work is rare, as most studies have applied an Almon weighting scheme, which places more emphasis on short-term patterns. However, oil shocks have a complex lag effect on GDP, often showing a delayed peak in the medium term. Ghysels et al. (2007) indicated that the Beta weighting function allows for a non-monotonic weighting distribution over the lags, thereby better capturing the relationship between oil shocks and GDP. The primary model considered in this paper is the TVP-AR-MIDAS model, where the autoregressive term is also considered. A model combination strategy, namely dynamic model averaging (DMA) approach, is also applied to further improve model accuracy. Fourth, we extend our analysis to forecast not only US GDP but also the economic activity of other regions around the world. In summary, our paper is expected to be a crucial complement to the macroeconomic forecasting research using oil price fluctuations.

The remainder of the paper is organized as follows: Section 2 provides a brief overview of the dataset used in the study. Section 3 details the empirical methodologies employed in the analysis. Sections 4, 5 and 6 presents the findings from various predictive analyses. Finally, Section 7 summarizes the main results, explores the policy implications, and offers concluding remarks.

2. Data and Variables

2.1 Variable Construction (Decomposed Oil Price Shocks)

Herrera et al. (2019) summarized that identifying the underlying sources of oil price changes on the US economy is meaningful. The oil price and the US economy are interconnected, and different oil shocks have different impact on economic activity. For instance, oil supply shock increases the overall production cost and tends to decrease US GDP, while oil demand shocks might positively affect the US economy. Therefore, treating the oil price changes as an overall exogeneous indicator to the US economy and merely considering the oil supply shocks might be misleading. To analyze the effects of global oil price fluctuations in a decomposed perspective based on its transmission mechanism to GDP, we follow Baumeister and Hamilton (2019) to construct four types of underlying oil shocks.

The oil supply shocks cover unexpected changes in crude oil production, which are independent of demand-side factors, defined by

$$OS(t) = q_t - a_{qp}p_t - X_{t-1}\beta_{os}$$

where q_t is the monthly growth rate of global crude oil production on time t, $q_t = 100\ln(\frac{Q_t}{Q_{t-1}})$; p_t is real price of oil, a_{qp} is the price elasticity of supply in the short term, and $X_{t-1} = [x_{t-1},\ x_{t-2}, \dots, x_{t-24}]'$ is the vector of lagged value of variables over previous two years.

The economic activity shock belongs to the demand-side shock, representing fluctuations in real global economic activity (global GDP growth, industrial production, etc.) that influence oil demand. Denote the real economic activity by y_t and its contemporaneous effect with oil production by a_{qy}, the economic activity shock can be obtained by

$$EA(t) = y_t - a_{qy}p_t - X_{t-1}\beta_{ea}$$

The rest two types of oil demand shocks can be calculated by real oil price (p_t), monthly growth rate of oil production (q_t), real economic activity (y_t) and changes in oil inventories (Δi_t). The oil consumption demand shocks negatively correlate with Δi_t and positively correlated with q_t, whereas the oil inventory demand shocks increase with Δi_t and decreasing with q_t. The former arises from shifts in consumer preferences, energy efficiency improvement or technological advancements, and the latter affect GDP by changes in oil storage levels. They can be evaluated by

$$OCD(t) = q_t - b_{qy}y_t - b_{qp}p_t - \Delta i_t - X_{t-1}\beta_{ocd}$$

$$OID(t) = \Delta i_t - c_1 q_t - c_2 y_t - c_3 p_t - X_{t-1}\beta_{oid}$$

2.2 Data Description

To achieve the study's objective, we use quarterly data for the index of real US GDP, and monthly data for Headline Consumer Price Index (CPI) and short-term official/policy interest rate as standard controls, from the Database of Global Economic Indicators (DGEI) of the Federal Reserve Bank of Dallas,[1] covering the period from 1981 Q1 to 2023 Q1. The DGEI includes a core sample of 40 countries with groupings include rest of the world (excluding the US) advanced (excluding the U.S.) and emerging. Besides the US, as part of our international coverage, we also present results for these three cases as well. The reader is referred to Grossman et al. (2014) for further details regarding the construction of the variables in the DGEI dataset. Meanwhile, the real GDP index is computed by scaling each year's real GDP relative to the 2005 level, i.e. $GDP\ Index_t = \frac{GDP_t}{GDP_{2005}} \times 100$. The oil price shocks are constructed following Baumeister and Hamilton (2019).[2] The summary statistics of the raw value as well as the differentiated value of macroeconomic variables are shown in Table 1.

(Insert Table 1 around here)

[1] https://www.dallasfed.org/research/international/dgei#tab1.

[2] The data is available for download from: https://sites.google.com/site/cjsbaumeister/datasets?authuser=0.

As the real GDP index and CPI are non-stationary, we obtain stationary time series by applying first-order differencing as shown below to eliminate data trends and enhance the stability of the MIDAS model:

$$\Delta X_t = X_t - X_{t-1}$$

where X_t denotes raw value the macroeconomic indices (real GDP index, CPI, policy rate and oil shocks) at time t. The raw value of the real GDP index and its differentiated value are shown in Figure 1.

(Insert Figure 1 around here)

3. Model

The Mixed Data Sampling (MIDAS) model differs from traditional time series regression models in its ability to handle data with heterogeneous observational frequencies. It is an ideal choice for modeling GDP alongside macroeconomic variables, as GDP is typically announced quarterly, whereas most macroeconomic data are available at a monthly frequency. Hence, in this study, we apply three prevalent MIDAS models for forecasting purposes, two of which incorporate time-varying model parameters.

3.1 Standard AR-MIDAS model

Before explaining the standard AR-MIDAS model, we first introduce the standard MIDAS model (std-MIDAS), which was first proposed by Ghysels et al. (2004). This model combines the lagged terms of high-frequency predictors using a specific weighting scheme to estimate the value of the low-frequency objective variable. The basic structure is

$$Y_{t+h} = \alpha + +\theta B\left(L^{\frac{1}{m}}; \omega\right) X_t^{(m)} + \epsilon_{t+h}$$

where $B\left(L^{\frac{1}{m}}; \omega\right) = \sum_{j=0}^{j_{max}} \delta(j;\ \omega)\, L^{\frac{j}{m}}$ is a polynomial that merges the information in the high-frequency macroeconomic indicators, and $\sum_{j=0}^{j_{max}} \delta(j;\ \omega) = 1$. Meanwhile, $L^{\frac{j}{m}} = X_{t-1-j/m}^{(m)}$ is a lagged operator, m is the number between t and $t-1$ due to the different time unit between quarterly data and monthly data. X_t is the vector of macroeconomic predictors at time t, h is the forecast horizon, $\epsilon_t \sim N(0, \sigma^2)$.

The std-MIDAS model assumes a fixed relationship between low-frequency and high-frequency macroeconomic variables (with θ being constant), and is therefore also known as the constant coefficient MIDAS model. While it is simple and computationally efficient, it is limited in its ability to capture changes in the dynamic relationship between macroeconomic predictors and the target variable. Since the stationary real GDP index series shows autocorrelation (see Table 1), we add an autoregressive term for GDP to construct the general form of the standard AR-MIDAS model, which is presented in Table 2.

3.2 Markov Regime Switching AR-MIDAS model

As the aforementioned literature indicates that the impact of crude oil price variables on the US real GDP changes over time, MIDAS models with time-varying parameters will be applied to forecast GDP. Guérin and Marcellino (2013) proposed a time-varying extension of the standard MIDAS model called Markov Regime Switching MIDAS model (MS-MIDAS). It integrates the Markov Regime Switching scheming framework into MIDAS, allowing the model parameters to vary across different market regimes. Typically, it is assumed that there are three distinct market regimes: recession, low expansion and high expansion. The structure as well as the parameter estimation algorithm of MS-AR-MIDAS model are also presented in Table 2.

3.3 Time Varying Parameter AR-MIDAS model

Pan et al. (2018) constructed a more flexible time-varying parameter MIDAS model, namely TVP-MIDAS. Unlike the discrete parameter changing scheme in MS-MIDAS, the coefficients of macroeconomic predictors of TVP-MIDAS can continuously vary with time. This allows the impact of macroeconomic predictors on GDP, especially oil shocks, to evolve smoothly with time. In their empirical study forecasting US GDP using oil price fluctuations, Pan et al. (2018) found that the TVP-MIDAS model outperforms both the Markov Regime Switching MIDAS (MS-MIDAS) and the standard MIDAS models. This paper further investigates whether the same conclusion holds when predicting GDP using structurally decomposed oil price shocks. The structure of the TVP-AR-MIDAS structure is also reported in Table 2.

(Insert Table 2 around here)

3.4 Weighting Scheme

As mentioned in 3.1, MIDAS incorporates information from high-frequency macroeconomic indicators using specific weighting schemes. The well-known scheme includes the Almon lag structure and the Beta lag structure. According to Ghysels et al. (2007), the Almon lag structure parameterizes the lagged weights using an exponential function, while the Beta lag structure uses a Beta function for this purpose. The former is commonly used in MIDAS models; its weights decrease as the lag increases, thereby capturing more of the short-term impact of macroeconomic predictors. In contrast, the Beta lag structure is a more flexible weighting scheme that can model non-monotonic relationships between the high-frequency and low-frequency variables.

Since the effects of oil price shocks on US real GDP are typically lagged, we use the beta lag structure in the MIDAS model as the weighting scheme to capture both short-term and long-term effects.

$$\delta(j;\ \omega, j_{max}) = \frac{\left(\frac{j}{j_{max}}\right)^{\omega_1}\left(1-\frac{j}{j_{max}}\right)^{\omega_2-1}}{\sum_{j=1}^{j_{max}}\left(\frac{j}{j_{max}}\right)^{\omega_1-1}\left(1-\frac{j}{j_{max}}\right)^{\omega_2-1}}$$

Based on the overall structure presented in **Table 2**, we construct a set of sub-models that include different macroeconomic indicators as the predictor vector X, to examine the impact of decomposed oil price shocks on the US GDP. We first build a baseline model consisting of CPI and the policy rate, and then add each oil shock individually to observe whether forecast performance improves. The macroeconomic indicators included in each sub-model are shown in **Table 3**.

(Insert Table 3 around here)

4. Empirical Study

In this section, we examine the effectiveness of the Std-MIDAS model, MS-MIDAS model TVP-MIDAS models, where the decomposed oil shocks are included simultaneously. In addition to comparing the different MIDAS models, we also analyze the forecasting ability of oil price shocks on US GDP based on the performance of the sub-models introduced in Table 3. Both in-sample fit and out-of-sample forecasting will be conducted. The former includes analysis of model parameters paths and goodness of fit, while the latter mainly focuses on forecasting accuracy.

4.1 In-sample Fit

We first conduct an in-sample fit for the group of models introduced in Section 3.3.2, considering different numbers of autoregressive terms for GDP (i.e., lagged values of y, denoted as ylag). The log-likelihood ($log\mathcal{L}$) is used to evaluate the goodness of fit of the models. Assuming that the error of the MIDAS models in this article is normally distributed, the log-likelihood function of in-sample fit is written as follows:

$$log\mathcal{L} = -\frac{T}{2}\log(2\pi\sigma^2) - \frac{1}{2\sigma^2}\sum_{t=1}^{T}(Y_t - \hat{Y}_t)^2$$

where $\hat{Y}_t$ is the fitted value, Y_t is the actual value, and σ^2 is the variance of the error. The model with larger log-likelihood is considered to have a better fit.

Table 4 shows the $log\mathcal{L}$ results of the three MIDAS models, grouped by the different macroeconomic predictors included. The TVP-AR-MIDAS model demonstrates the best fit across different numbers of autoregressive lags (ylag) compared to the Standard-AR-MIDAS and MS-AR-MIDAS. Among the sub-models with different decomposed oil shocks, those including economic activity shocks perform best, outperforming the benchmark across all MIDAS models and ylag values, except for the MS-AR-MIDAS when ylag equals 2, showing its significant impact of economic activity shocks on US GDP. The in-sample fit of sub-models incorporating oil consumption demand shocks and oil inventory demand shocks is also remarkable in the TVP-AR-MIDAS and MS-AR-MIDAS model, whereas their importance is negligible in the Standard-AR-MIDAS model.

(Insert Table 4 around here)

In addition to evaluating goodness of fit, the coefficient paths of the time-varying MIDAS models (MS-AR-MIDAS and TVP-AR-MIDAS) can also be obtained from the in-sample fit process. This allows us to analyze the impact of decomposed oil shocks on US GDP, differentiated by the included number of autoregressive terms.

Regarding the MS-AR-MIDAS model, the coefficients of the macroeconomic predictors vary discretely across different market regimes. Figure 2 presents the smoothed transition probabilities of market regimes in the MS-MIDAS models with different oil shocks, where the grey shaded areas represent recession periods identified by the National Bureau Economic Research (NBER). Both economic activity shocks and oil inventory demand shocks impact heavily on US GDP, as the transition probabilities of the MS-AR-MIDAS models incorporating these two oil shocks under the recession market regime largely match the actual recessions indicated by the NBER. Furthermore, the regime-switching probabilities tend to shift before the onset of actual recessions, suggesting that these two oil shocks provide predictive foresight into recessions. For example, when two autoregressive terms are included, the model incorporating economic activity shocks is able to predict the debt crisis of the 1980s, the subprime mortgage crisis in 2008 and the COVID-19 recession in 2020. The oil supply shock also captures the recession periods effectively when ylag is 0 or 1, but tends to miss the historical recession periods when more autoregressive terms are included.

(Insert Figure 2 around here)

Figure 3 illustrates the in-sample coefficient paths in the TVP-AR-MIDAS model. The effects of different oil shocks diverge significantly, as seen with the oil consumption demand shock and the oil inventory shocks when ylag = 0. The coefficient path of the same macroeconomic predictor also shows heterogeneity across different ylags and models. For example, oil supply shocks negatively impact the US GDP in certain periods when ylag is 0 or 1, whereas a positive relationship between them occurred when ylag equals 2 or 3. Economic activity shocks show a significant negative correlation with the US macroeconomy when the number of ylag is 0 or 1, which reverses to a positive relationship when ylag is larger than 1. The influence of oil inventory demand shocks on the objective variable remains consistently negative, although the magnitude of the effect varies across different number of autoregressive terms.

Beyond the heterogeneity of coefficients across different numbers of autoregressive terms, the coefficients of these macroeconomic predictors also exhibit time-varying patterns. The coefficient path of the oil consumption demand shock is a good example. When the autoregressive term is included, the coefficient of oil consumption demand shocks fluctuates between positive and negative values initially, but remains positive after the third quarter of 1995. The effect of oil inventory demand shocks is more significant in the 20th century compared to the 21st century.

(Insert Figure 3 around here)

4.2 Out-of-sample Forecasts

Since US GDP is announced quarterly, the data from 1981 Q1 to 2023 Q1 contains a limited number of observations. Hence, we conducted the out-of-sample forecast of US GDP recursively to reduce the bias, using an initial window size of 40 quarters. Consistent with the in-sample fit, models with four different number of autoregressive terms for US GDP (ylag = 0, 1, 2, 3) were considered. We also set different forecast horizons (including 1/3, 2/3, 1, 2, 3 quarters[3]) to perform both short-term nowcasting and long-term forecasting on US GDP. Hence, the data for high-frequency macroeconomic predictors was required to start in 1980 Q2 to fulfill the data requirements for prediction.

To evaluate the forecast accuracy of different MIDAS models and decomposed oil shocks, three evaluation metrics (MSE, MAE and MAPE) are used. MSE involves squaring the forecast errors, making it sensitive to outliers. MAE considers the absolute value of forecast error, making it more robust than MSE, although it is less effective at penalizing large errors. MAPE calculates the relative error over the actual value, but it may be singular when the actual value is close to 0. Hence, we incorporate all three metrics to conduct a comprehensive out-of-sample analysis. Smaller values of these metrics indicate grater prediction accuracy.

[3] Forecast horizon is 1/3, 2/3 quarter means the monthly indicators up to the second month and the first month in this quarter are used for forecasting the quarterly GDP respectively. See Chan et al. (2024), Guérin & Marcellino (2013) for more details.

$$MSE = \frac{1}{T}\sum_{t=1}^{T}(Y_t - \hat{Y}_t)$$

$$MAE = \frac{1}{T}\sum_{t=1}^{T}\left|Y_t - \hat{Y}_t\right|$$

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right|$$

The forecast performance of all models with different number of autoregressive terms and different forecast horizons are shown in Table 5. Similar to the in-sample fitting results, the MIDAS models that allow parameters to vary with time have an overall better performance than those that incorporate constant coefficients, especially the TVP-MIDAS model, which has a significantly lower forecast error than the other two MIDAS models. Even though the std-AR-MIDAS model reaches the highest forecast accuracy in some cases when ylag is 0 or 1, it is less effective at capturing the relationship between decomposed oil shocks and US GDP, as fewer sub-models that include oil shocks outperform the benchmark compared to the MS-AR-MIDAS model and TVP-AR-MIDAS model.

With respect to the sub-models that include various decomposed oil shocks, the TVP-AR-MIDAS models incorporating economic activity shocks and oil inventory demand shocks perform the best. The TVP-AR-MIDAS-EA model achieves a MAPE of only 0.7907, while the MAE of the TVP-AR-MIDAS-OID is reduced to 0.5952 when the number of autoregressive terms is 2. These results highlight the significance of demand-side oil shocks, which challenges the traditional view that most oil price fluctuations come from the supply side. The sub-models incorporating oil supply shocks and oil consumption demand shocks perform better in short-term forecasts (forecast horizons of one quarter or less).

(Insert Table 5 around here)

Figure 4 illustrates the out-of-sample forecast results of the models based on a comprehensive ranking that incorporates all the three evaluation metrics discussed above. The superiority of the TVP-AR-MIDAS model is evident in both short-term and long-term forecasts, especially when ylag is not equal to 0. The models that include economic activity shocks and oil inventory demand shocks have higher forecast ability for US GDP, particularly when time-varying parameters are incorporated. When ylag is 0 or 1, the model with economic activity shocks achieves higher accuracy in middle-term (i.e. h=1 quarter) forecasting compared to the benchmark, and it performs well in long-term forecasts when ylag is 2 or 3. The oil inventory demand shock exhibits a stronger correlation with long-term US GDP, except in the case where ylag is equal to 1. The other two shocks are less significant in predicting GDP overall, but they still play important roles in specific scenarios. For example, the oil supply shock is significant for forecasting short-term GDP, and its middle-term predictability outperforms the benchmark when 3 autoregressive terms are included. Similarly, the model considering oil consumption demand shocks also achieves higher accuracy than the benchmark in both middle and long-term forecasts when ylag is 2 or 3.

(Insert Figure 4 around here)

4.3 Robustness Test

To verify the robustness of the models under different settings, we change the initial window size and the forecast horizons of the recursive forecast process and examine whether the model performance diverged from the results above. We try four different initial window sizes of 20, 30, and 50 quarters respectively, and also consider scenarios with longer forecast horizons of 4 and 8 quarters. The robustness test results are shown in the table in the appendix. Overall, the conclusions drawn from the robustness tests are consistent with the results discussed above, indicating that our model performance is robust across different empirical settings.

5. Further Analysis

To identify which oil shock has the greatest impact on US GDP, one technique is to compare the in-sample coefficient paths and the out-of-sample forecast performance of the alternative models mentioned above. Another approach is to apply a model combination strategy and to analyze the inclusion probabilities of sub-models with different oil shocks. A higher inclusion probability for sub-model with a specific oil shock means that this shock has a significant impact on US GDP. The Dynamic Model Averaging (DMA) approach is a well-known model combination strategy that dynamically incorporates the best predictions from candidate models. In this section, we apply the DMA strategy to evaluate forecast performance and further discuss the effect of oil shocks on US GDP using the inclusion probabilities of the sub-models. The performance of DMA models based on different MIDAS structures will also be compared.

5.1 Dynamic Model Averaging Strategy

According to Raftery et al. (2010), the DMA model can be written as a state space model with a regression form

$$y_t = x_{t,k}\theta_{t,k} + \epsilon_{t,k}$$
$$\theta_{t,k} = \theta_{t-1,k} + \delta_{t,k}$$

where $\sim N(0, \sigma_k)$, $\delta \sim N\left(0, W_{t,k}\right)$. The overall h-step-ahead prediction of the US GDP by DMA is

$$GDP_t = \sum_{k=1}^{K} \pi_{t|t-h,k} X_{t-h,k}^{T} \hat{\theta}_{t-h,k}$$

where $\pi_{t|t-h,k}$ is the inclusion probability of model k at time t and it is updated by

$$\pi_{t|t,k} = \frac{\omega_{tk}}{\sum_{l=1}^{K} \omega_{tl}}$$

$$\omega_{tl} = \pi_{t|t-h,l} f_l(y_t|Y_{t-h})$$

L_t is the model indicator, $Y_{t-h} = \{GDP_1, GDP_2, \dots, GDP_{t-h}\}$, $X_{t-h,k}^{T}$ is the matrix of all the predictors of model k, and $\hat{\theta}_{t-h,k}$ is the corresponding time varying coefficients. All the parameters of the DMA are estimated through MLE based on Kalman's filter. In this article, the candidate models are the MIDAS model with single oil shocks introduced in Table 3, hence K=4. The forgetting parameters are set to 0.95.

5.2 Model Performance

In the dynamic model averaging process, we combine the sub-models with different oil shocks under the same MIDAS structure by assigning specific weights to them. Therefore, we generate three DMA models, namely DMA-Std-AR-MIDAS, DMA-

MS-AR-MIDAS and DMA-TVP-AR-MIDAS. Their out-of-sample forecast accuracy will be compared with that of single MIDAS models with the same structure to assess whether applying the DMA approach improves overall performance. Additionally, the DMA models will be compared with each other to identify the MIDAS specification with the best predictive accuracy.

From Table 6, we can observe that the model averaging strategy significantly improves forecast accuracy, as most DMA models outperform the benchmark and achieve higher accuracy compared to the single MIDAS model. Although the single MIDAS models that incorporate oil supply shock and the economic activity shock also demonstrate significant forecasting performance, they are less robust than the DMA models across different empirical settings. While the majority of DMA models under the standard AR-MIDAS framework exhibit superior forecasting accuracy relative to the benchmark, their performance is exceeded by some individual models, especially when the forecast horizon is long. The DMA models that incorporate the MS-AR-MIDAS and the TVP-AR-MIDAS structure tend to be more stable across various forecast horizons.

(Insert Table 6 around here)

The out-of-sample performance of DMA models under different MIDAS structures is shown in Table 7. It can be observed that the model that incorporates the TVP-AR-MIDAS model achieves the best forecast performance compared to the other two DMA models in most cases. This result highlights the strength of the TVP-AR-MIDAS, as the continuous time-varying parameters allows the weights of the decomposed oil shocks vary with time, which is more realistic and increases the model flexibility. The DMA model under the standard MIDAS structure has slightly lower MSE and MAE than the DMA-TVP-AR-MIDAS when the number of autoregressive terms is 0, which may contribute to the overfitting, but the MAPE of the latter is still higher. It is also worth mentioning that the forecast performance of DMA-MS-AR-MIDAS is not ideal. The underlying reason may come from the mechanism of DMA itself. Introduced in Section 5.1, DMA selects the best-performing model through a model-switching dynamic; hence, model complexity increases if the candidate model already exhibits a time-varying pattern, especially in the case of the MS-MIDAS structure.

(Insert Table 7 around here)

5.3 The Effect of Oil Shocks

Having analyzed the forecast performance of DMA models, we now discuss the importance of the decomposed oil shocks by extracting and analyzing the inclusion probability of each sub-model incorporating different oil shocks. The inclusion probabilities (a.k.a. DMA weights) for all the three DMA models under different MIDAS structures are considered. Overall, the DMA weight of the std-MIDAS sub-models (see Figure 5) is the most stable one, whereas those of sub-models with time-varying parameters are much more dispersed (see Figure 6, 7). Compared to DMA-TVP-AR-MIDAS model, the pattern of the weights of the DMA-MS-AR-MIDAS model is more discrete and is more remarkably influenced by recessions. Based on the results in the last section, we mainly discuss the effect of oil shocks based on the inclusion probabilities of the DMA-TVP-AR-MIDAS model. Figure 7 shows the inclusion probabilities of each TVP-AR-MIDAS sub-model incorporating different decomposed oil shocks within the DMA framework. Overall, the economic activity shock has a significant impact on the US economy, as the DMA assigns the largest weight to the sub-model that incorporates this decomposed shock in most cases, even reaching 0.4 when ylag is 1, and the forecast horizon is 1 month. The impact of oil supply shocks on US GDP is also emphasized by the DMA, especially in long-term forecasts. The sub-model of oil inventory demand shocks tends to have higher DMA weights after the COVID-19 recession. Furthermore, the effects of oil shocks appear to be closely correlated with the economic cycle, as the inclusion probabilities of sub-models with different oil shocks remarkably jump during recession periods. For instance, when the forecast horizon is 1 month and no autoregressive term is included, the economic activity and oil supply shocks play significant roles in forecasting US GDP before the pandemic, with DMA weights of 0.27 and 0.26, respectively. However, the importance of these two shocks declines substantially after 2020, while the oil inventory demand shock becomes the most important factor, with its DMA weight rising from 0.25 to nearly 0.3.

Compared to DMA-TVP-AR-MIDAS, the inclusion probabilities of sub-models in DMA-std-AR-MIDAS and DMA-MS-AR-MIDAS are less robust across different scenarios (see Figure 5, 6). In Figure 5, the DMA under std-MIDAS structure tends to assign similar weights to the sub-models containing decomposed oil shocks before the pandemic period. However, after 2020, the importance of oil shocks significantly diverges. In short-term forecasts, the model incorporating economic activity shocks is assigned large weight by the DMA, whereas in long-term forecasts, oil inventory demand shocks and oil consumption demand shocks become the key drivers of US GDP. The DMA weights under the MS-AR-MIDAS structure display an extremely diverged pattern. The inclusion probability of sub-models with important oil shocks is close to 1, while that of sub-models with insignificant oil shocks is reduced to 0. In some specific cases, the DMA weights of different sub-models can completely reverse after a recession. For example, when the forecast horizon is 2 months and the number of autoregressive term is 1, the oil inventory demand shock initially plays an important role, then is substituted by the oil consumption demand shock, and finally the economic activity shock becomes the most influential factor for US GDP.

Our results verify the recent discovery regarding the influence of crude oil price fluctuations on GDP. Some traditional points of view assume that the impact of crude oil price fluctuation on GDP is exogeneous and mainly comes from the supply-side. However, our results illustrate that the oil supply shock is merely one of the several driving factors affecting GDP, and its the effects are negligible compared to other shocks in certain scenarios (e.g., when the forecast horizon is h=1 and ylag=2). This finding provides strong evidence that complements the conclusions of Barsky and Kilian (2001) and Baumeister and Hamilton (2019), who argue that economic activity shocks and demand-driven shocks in crude oil price fluctuations are significant determinants of macroeconomic performance.

(Insert Figures 5, 6 and 7 around here)

6. International Evidence

Having analyzed the effects of oil shocks on GDP in the US, we expand our discussion to other regions in the world to discuss the regional heterogeneity of the impact of oil price shocks. In this Section, we examine the forecast ability of models and the explanatory capability of oil shocks on the GDP of the world (excluding US), advanced countries (excluding the US) and the emerging countries. All data, along with corresponding controls of CPI and short-term policy rates are obtained from the DGEI.

From Tables 8, 9 and 10, the TVP-MIDAS model generally yields superior out-of-sample forecasts across all three regions, consistent with the results for the US. Although some sub-models under the std-MIDAS yields the best accuracy when the number of ylag is small, the forecast errors of TVP-MIDAS model are significantly lower than those of the other two models, and most sub-models under this structure rand first in the evaluation metrics. The superiority of the TVP-MIDAS models with large number of ylags also verifies its ability to capture the complex relationship between the predictors and the objective variables over time. Overall, the results in this section further underpins the effectiveness of the TVP-MIDAS model in explaining the sophisticated time-varying impacts of oil shocks on the macroeconomic outcomes.

Notably, the specific sub-model consisting of different oil shocks shows heterogeneity across regions. At the global level, the impact of supply-side oil and demand-side oil shocks are relatively balanced. However, emerging economies exhibit greater sensitivity to supply-side shocks, whereas demand-side shocks play a more dominant role in advanced regions (excluding the US). In those regions except the US, sub-models incorporating oil supply shocks achieve significant accuracy, especially in the emerging areas. Conversely, in advanced economies (excluding the US), oil demand shocks have a more substantial impact. This pattern may reflect the relative independence of other advanced economies, particularly the US, in oil supply due to their evolving role in global oil markets (Herrera et al., 2019), rendering them more susceptible to demand-side shocks such as economic activity shocks and oil inventory demand shocks. In contrast, most emerging economies remain heavily reliant on oil imports, making them more vulnerable to supply-side shocks. As summarized by Cepni et al. (2022), supply-side shocks tend to have significant and persistent impacts on oil-importing countries, underscoring the continued vulnerability of emerging regions to such shocks.

(Insert Tables 8, 9 and 10 around here)

7. Conclusions

This paper investigates the predictability of supply and demand oil price shocks on U.S. GDP using several MIDAS models which relate quarterly GDP with monthly oil price shocks for the period 1981-2023. Following the literature, we decompose oil price shocks into supply, economic activity, oil consumption demand and oil inventory shock, in order to better understand the main mechanisms driving the impact of oil price shocks on economic activity. MIDAS models with constant coefficients, as well as those with discrete and continuous time-varying coefficients are used in the empirical analysis, and the results show that the TVP-MIDAS structure captures the relationship between monthly macroeconomic predictors and quarterly US GDP most effectively. We also apply Dynamic Model Averaging (DMA) to effectively combine single MIDAS models with different oil shocks. Beyond enhancing forecasting accuracy, this approach allows for an in-depth analysis of oil shock effects through coefficient paths, empirical comparisons with benchmarks, and the inclusion probabilities of sub-models within DMA.

Our main results can be summarized as follows. First, they suggest that the traditional approach of treating oil price fluctuations as a single exogenous variable for forecasting GDP is biased, as the economic impact of oil price changes differs depending on whether they are driven by supply-side or demand-side shocks. For example, and for the US case, oil demand shocks have higher forecast ability than oil supply shocks, highlighting the importance of disentangling oil price shocks into their components. Second, oil price shocks exhibit heterogeneous effects across time and forecast horizons. Among these shocks, economic activity shocks generally have the most significant impact on US GDP, as evidenced by the in-sample fit, out-of-sample forecast performance, and the inclusion weights of the corresponding sub-models in the DMA analysis. Third, the TVP-AR-MIDAS framework outperforms both the standard AR-MIDAS and MS-AR-MIDAS models in forecasting US GDP using oil shocks. While the MS-AR-MIDAS model achieves lower accuracy than the standard AR-MIDAS, it demonstrates greater robustness across varying conditions. Fourth, applying a model combination strategy can remarkably improve forecast accuracy, especially for the DMA model under the TVP-AR-MIDAS structure. These findings complement the existing macroeconomic forecasting research from both model and variable perspectives, which improves the forecasting accuracy and provides an innovative perspective regarding the underlying economic mechanism behind the US GDP. Finally, we extend our analysis to other regions in the world and the results suggest that while oil demand shocks play a significant role in forecasting economic activity in other advanced regions, the emerging regions are more vulnerable to oil supply shocks.

This study provides several future research directions. Having mentioned the limited performance of DMA that combines the MS-AR-MIDAS structure, our methodology, especially the DMA-MIDAS model, can be further extended by the integration of feature engineering such as LASSO, Elastic net, etc. to balance forecast accuracy and the model complexity. Moreover, besides decomposed oil shocks, we can also explore other potential macroeconomic variables that may impact on the US GDP.

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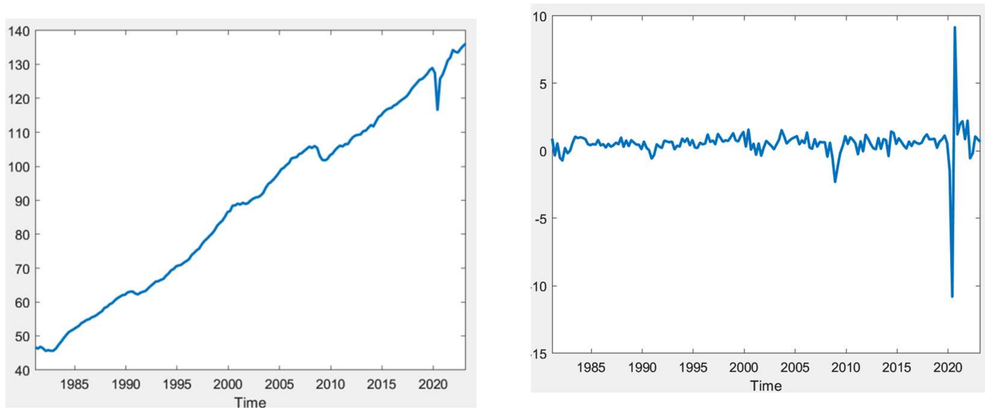
Figures and Tables

Table 1 Summary Statistics of Macroeconomic Variables

		Time	Frequency	Mean	StdDev	Skewness	Kurtosis	ADF	Q(5)	Q(10)
Raw Value	Real GDP Index	1981.3-2023.3	Quarterly	88.6382	26.6011	-0.0042	1.7579	5.3747	778.8685***	1432.8311***
	CPI			92.9477	28.1961	0.0967	1.9495	17.4059	2443.3517***	4723.4036***
	Policy Rate			4.1631	3.7666	1.1048	4.5401	-4.3641***	2283.5837***	4105.6829***
	Oil Supply Shock (OS)	1981.1-2023.3	Monthly	-0.0650	1.3825	-1.4004	13.0053	-20.2913***	7.4061	10.1497
	Economic Activity (EA)			-0.0224	0.6952	-2.0903	25.8823	-22.8402***	0.3865	1.4452
	Oil Consumption Demand Shock (OCD)			-0.1308	3.7550	-0.3042	4.3999	-21.2673***	1.8370	5.0800
	Oil Inventory Demand Shock (OID)			-0.0142	1.1109	0.2424	3.1937	-24.0594***	3.3503	5.4936
First-Order Differencing	Real GDP Index	1981.3-2023.3	Quarterly	0.5347	1.2396	-2.6587	56.4180	-13.0430***	7.5143	9.5276
	CPI			0.2166	0.2912	-0.2324	13.8400	-9.5437***	207.8553***	272.6269***
	Policy Rate			-0.0274	0.3758	-1.5915	24.7818	-14.9564***	84.5213***	146.7407***
	Oil Supply Shock (OS)	1981.1-2023.3	Monthly	-0.0024	1.8568	-0.2146	11.3887	-36.3676***	106.0297***	112.7303***
	Economic Activity (EA)			-0.0006	0.9913	0.8936	21.4444	-38.9304***	127.8140***	128.3971***
	Oil Consumption Demand Shock (OCD)			-0.0080	5.1689	0.0190	3.3567	-37.1080***	111.1687***	118.0120***
	Oil Inventory Demand Shock (OID)			0.0014	1.6235	0.1846	3.3376	-40.5301***	141.9490***	144.2252***

Note: ADF result with '***' means the time-series is stationary at 0.01 significance level; Q(5), Q(10) result with '***' means the time-series is free from autocorrelation at 0.01 significance level in 5-lag Ljung-Box test and 10-lag Ljung-Box test respectively.



(a) Raw value of real GDP

(b) First-order differencing real GDP

Figure 1 The Trend of US Real GDP

Table 2 Structure and parameter estimation of MIDAS model

MIDAS Model	Structure	Parameter Estimation
Std-AR-MIDAS	$$Y_{t+h}=\alpha+\sum_{i=0}^{ylag}\lambda_i Y_{t-i}+\theta B\left(L^{\frac{1}{m}};\omega\right)X_t^{(m)}+\epsilon_{t+h}$$ where $\sum_{i=0}^{ylag}\lambda_i Y_{t-i}$ is the autoregressive term of GDP, $ylag=\{0,1,2,3\}$ is the number of autoregressive term of GDP, $X_t^{(m)}$ is the vector of macroeconomic indicators with lag m, $m=3$. $B\left(L^{\frac{1}{m}};\omega\right)$ is a polynomial (see 3.1 for more details). θ is the coefficient of predictors $X_t^{(m)}$, h is the forecast horizon, α is the intercept, $\epsilon_t \sim N(0,\sigma^2)$. Meanwhile, θ, λ, σ and α are constant over time.	Depending on the data and sample size, the parameter can be estimated through nonlinear least squares, maximum likelihood function, generalized method of moments, etc. (Ghysels et al., 2004). We take the maximum likelihood function as an example $$\max_{\gamma}\sum_{t=1}^{T} lnf(\gamma_{t+1})$$ where γ includes θ, σ, λ and α, f is the log-likelihood function that $$f(\gamma_{t+1})=\frac{1}{\sqrt{2\pi\sigma^2}}\exp(-\frac{1}{2\sigma^2}\left(Y_t-\hat{Y}_t\right)^2)$$
MS-AR-MIDAS	$$Y_{t+h}=\alpha(S_t)+\sum_{i=0}^{ylag}\lambda_i Y_{t-i}+\theta(S_t)B\left(L^{\frac{1}{m}};\omega\right)(1-\sum_{i=0}^{3}\lambda_i)X_t^{(m)}+\epsilon_{t+h}(S_t)$$ where all the α, θ and ϵ are function of $S_t=\{1,2,\dots,M\}$, which denotes market regime at time t, defined by typical transition probabilities $$p_{kl}=\Pr(S_{t+1}=l\mid S_t=k)$$ $$\sum_{l=1}^{M} p_{kl}=1\ \forall\ k,l\in\{1,2,\dots,M\}.$$	The objective of estimating parameter by maximum-likelihood function is $$\max_{\gamma}\sum_{t=1}^{T} lnf(\gamma_{t+1}\mid\Omega_t)$$ where $$f(\gamma_{t+1}\mid\Omega_t)=\sum_{l=1}^{M}\Pr(S_{t+1}=j\mid\Omega_t)\,f(\gamma_{t+1}\mid S_t=j,\Omega_t)$$
TVP-AR-MIDAS	$$Y_{t+h}=\alpha+\sum_{i=0}^{ylag}\lambda_i Y_{t-i}+\theta(\tau_t)B\left(L^{\frac{1}{m}};\omega\right)\left(1-\sum_{i=0}^{3}\lambda_i\right)X_t^{(m)}+\epsilon_{t+h}$$ where λ, σ and α are constant, while $\theta(\tau_t)\approx a_0+a_1(\tau_t-\tau_0)$ is a function of time, describing the changed effect of macroeconomic indicators to GDP in different period, $\tau_t=\frac{t}{T}$.	Following Pan et al. (2018), we use a local maximum likelihood estimation defined by $$\max_{\gamma}\sum_{t=1}^{T} lnf(\gamma_{t+1})K_b(\tau_t-\tau_0)$$ where $K_b(x)=\frac{K\left(\frac{x}{b}\right)}{b}$ is kernel function, b is bandwidth.

Table 3 The inclusion of macroeconomic indicators of MIDAS sub-models

	CPI	Policy Rate	Oil Supply Shock	Economic Activity Shock	Oil Consumption Demand Shock	Oil Inventory Demand Shock
Benchmark	○	○				
OS	○	○	○			
EA	○	○		○		
OCD	○	○			○	
OID	○	○				○

Note: the first column indicates different MIDAS sub-models, ○ means the model includes the macroeconomic indicators in X_t.

Table 4 The log-likelihood of in-sample fit across different models

	ylag = 0			ylag = 1			ylag = 2			ylag = 3		
	Standard-AR-MIDAS	MS-AR-MIDAS	TVP-AR-MIDAS	Standard-AR-MIDAS	MS-AR-MIDAS	TVP-AR-MIDAS	Standard-AR-MIDAS	MS-AR-MIDAS	TVP-AR-MIDAS	Standard-AR-MIDAS	MS-AR-MIDAS	TVP-AR-MIDAS
benchmark	-255.6559	-125.3549	**-94.7963**	-249.2422	-112.5486	**-91.2291**	-247.7190	-99.4364	**-88.7070**	-240.9729	-107.2471	**-85.9950**
OS	-258.0010	-114.1447	**-94.6931**	-255.6655	-118.4270	**-91.1467**	-254.6193	-107.5966	**-88.7271**	-252.9138	-107.0493	**-85.9847**
EA	-233.1432	-103.1930	**-84.4509**	-226.1877	-89.3934	**-79.5453**	-224.8207	-103.7521	**-77.4413**	-221.2688	-76.3330	**-74.3838**
OCD	-259.2587	-120.5579	**-93.1731**	-255.2519	-111.9619	**-90.4339**	-254.2676	-96.3139	**-87.7005**	-252.5112	-114.0132	**-85.0166**
OID	-258.8441	-109.0892	**-89.9998**	-254.4179	-110.2370	**-86.9345**	-253.7541	-111.7008	**-85.3568**	-251.9645	-106.3371	**-83.1505**

Note: the grey-shaded results represent the corresponding model has better fit than the benchmark; the bold results show the best fit across all the three MIDAS models).

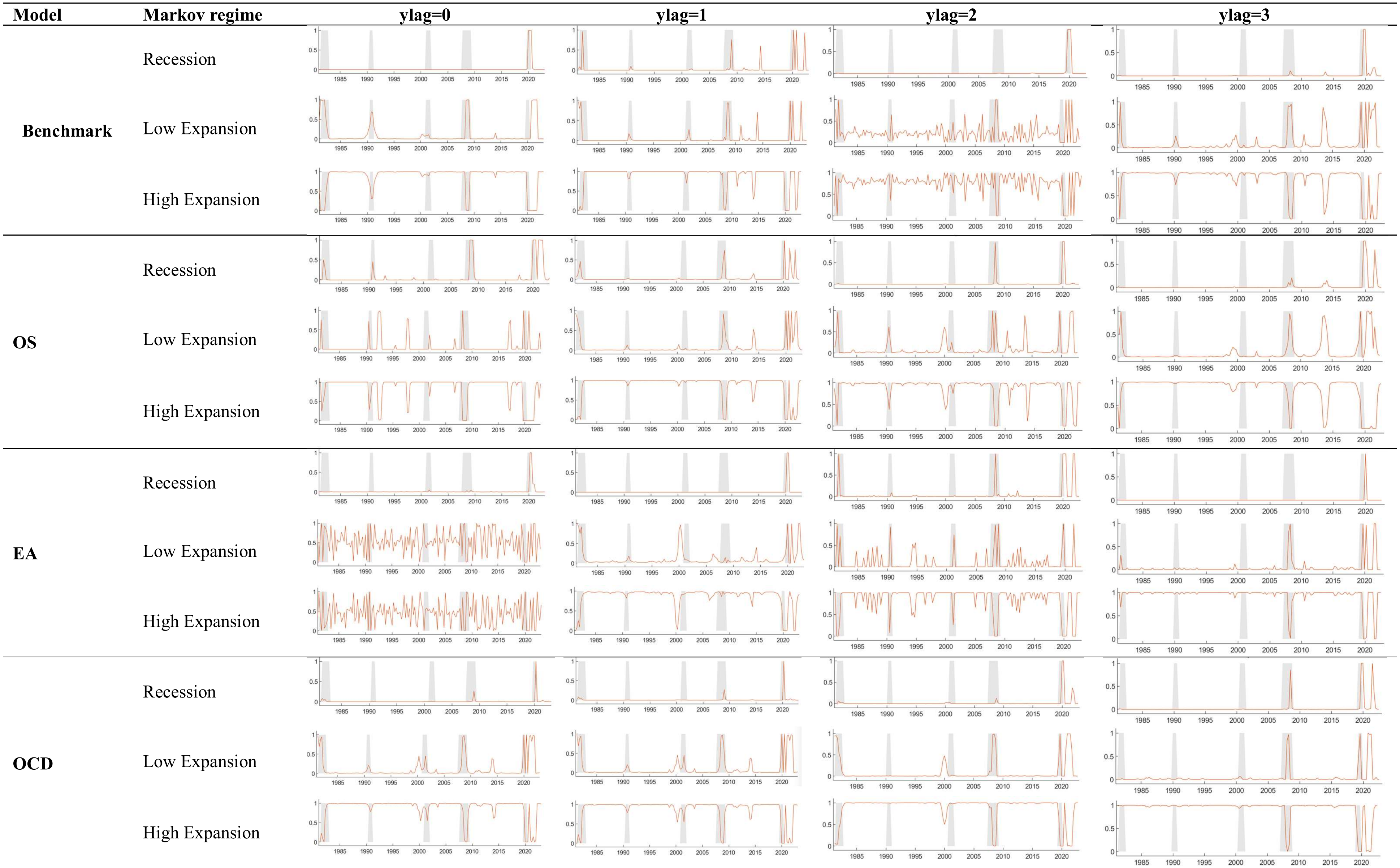


Figure 2 Smoothed switching probability of different Markov regime in MS-MIDAS model

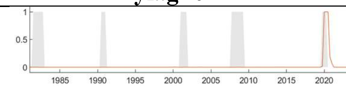
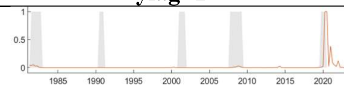
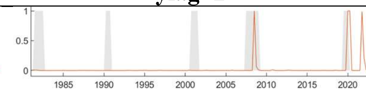
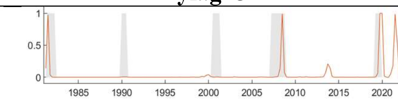
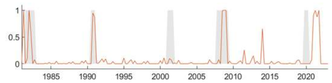
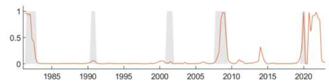
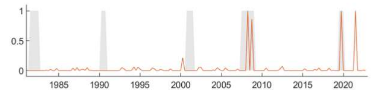
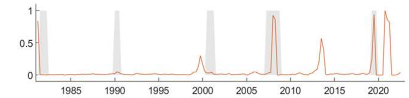
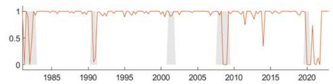
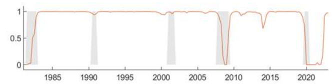
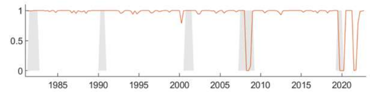
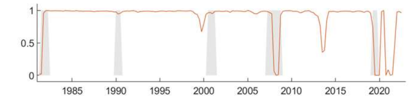
Model	Markov regime	ylag=0	ylag=1	ylag=2	ylag=3
	Recession				
OID	Low Expansion				
	High Expansion				

Figure 2 Smoothed switching probability of different Markov regime in MS-MIDAS model (continued)

Figure 3 The coefficient path of the predictors in TVP-MIDAS model

Table 5 Summary of out-of-sample forecast performance

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=1/3	MSE	ylag = 0	1.8318	1.8510	**1.4575**	1.8529	1.8087	4.0968	3.5610	5.7114	19.5150	6.5347	1.9933	1.9962	1.9923	1.9996	1.9966
		ylag = 1	3.0351	3.1444	2.2585	3.0896	3.0365	5.6842	2.5382	2.6319	29.5867	7.5801	2.0484	**2.0480**	2.0537	2.0566	2.0594
		ylag = 2	3.2216	3.3382	2.5548	3.2828	3.2258	**1.6846**	5.4836	7.7701	12.2756	30.5052	2.0636	2.0541	2.0631	2.0604	2.0616
		ylag = 3	3.5177	3.6812	2.8113	3.5933	3.5163	2.9338	3.8165	2.4692	15.2229	6.8399	2.0641	**2.0556**	2.0599	2.0614	2.0624
	MAE	ylag = 0	0.5741	0.5717	**0.5330**	0.5779	0.5682	1.0962	1.1702	1.1999	2.4896	1.3956	0.6190	0.6238	0.6187	0.6215	0.6189
		ylag = 1	0.6470	0.6474	**0.5886**	0.6514	0.6426	0.9292	0.8648	0.9014	2.1895	1.1986	0.6079	0.6073	0.6120	0.6141	0.6084
		ylag = 2	0.6719	0.6737	0.6239	0.6759	0.6680	0.6440	1.0570	1.0272	3.3799	1.3367	0.6090	0.6106	0.6122	**0.6056**	0.6082
		ylag = 3	0.7110	0.7143	0.6666	0.7156	0.7078	0.8020	1.0803	0.8654	1.9194	1.1068	0.6145	0.6187	**0.6107**	0.6166	0.6158
	MAPE	ylag = 0	2.4311	3.1539	1.3377	3.0432	7.0740	4.5017	5.3144	5.9604	4.8793	8.1620	0.8076	0.8151	0.8088	**0.8066**	0.8084
		ylag = 1	1.1663	1.2021	1.6772	1.1601	1.1595	2.4022	4.7277	3.1409	3.1528	9.2685	0.8240	**0.8186**	0.8290	0.8324	0.8277
		ylag = 2	1.1877	1.0820	**0.9183**	1.1242	1.1492	3.5400	4.2112	5.0876	2.1413	31.2946	0.7815	0.7940	0.7921	0.7822	0.7974
		ylag = 3	1.2898	1.2903	1.0090	1.2911	4.4308	4.2772	2.6336	3.1651	2.5402	3.4687	0.8178	0.8223	**0.8099**	0.8279	0.8361
h=2/3	MSE	ylag = 0	1.9514	1.8870	3.0967	**1.8640**	1.9629	2.6964	7.7305	3.5896	65.6119	5.3208	2.0025	2.0008	2.0023	2.0081	2.0033
		ylag = 1	3.7977	3.6559	5.1663	3.4544	3.8132	2.9060	7.8936	2.2497	15.8801	4.9296	2.0957	2.0932	2.0943	2.0983	**2.0291**
		ylag = 2	4.0428	3.8821	5.5338	3.6713	4.0602	3.2992	**1.1147**	3.2321	16.6698	8.2684	2.0808	2.0826	2.0496	2.0282	2.0884
		ylag = 3	4.3771	4.2142	5.9944	3.9637	4.3951	4.7079	3.8999	4.1462	12.7339	9.4421	2.0831	2.0848	2.0803	**2.0539**	2.0846
	MAE	ylag = 0	0.5793	0.5867	0.6398	**0.5748**	0.5857	0.8942	1.4172	1.0516	2.5658	1.2295	0.6314	0.6305	0.6312	0.6369	0.6315
		ylag = 1	0.6754	0.6718	0.7167	0.6600	0.6793	0.8583	1.1361	0.8449	2.0358	1.0874	0.6085	0.6072	0.6085	0.6141	**0.6020**
		ylag = 2	0.7136	0.7119	0.7608	0.6953	0.7172	0.8086	1.2365	0.8942	6.4828	1.1558	0.6136	**0.6095**	0.6133	0.6137	0.6146
		ylag = 3	0.7535	0.7502	0.8078	0.7341	0.7565	0.9213	1.0078	0.9917	1.7733	1.3550	0.6148	**0.6116**	0.6162	0.6191	0.6127
	MAPE	ylag = 0	1.3705	4.9552	2.5414	1.4270	1.3803	5.5205	4.2950	7.7637	13.2516	7.3517	0.8099	0.8213	**0.8096**	0.8327	0.8107
		ylag = 1	2.0722	2.6840	3.4831	2.5815	3.4454	2.5898	2.3493	3.5319	3.4448	29.1160	0.8334	0.8464	**0.8331**	0.8607	0.8357
		ylag = 2	1.3381	1.6188	2.2034	1.4650	1.4135	2.8201	**1.1014**	6.4206	2.5814	5.8094	0.8102	0.8272	0.8187	0.8299	0.8225
		ylag = 3	1.5577	1.8659	1.8708	1.6981	1.5337	2.3929	2.9301	2.4980	4.2112	4.4241	0.8188	0.8293	0.8205	0.8422	**0.8130**

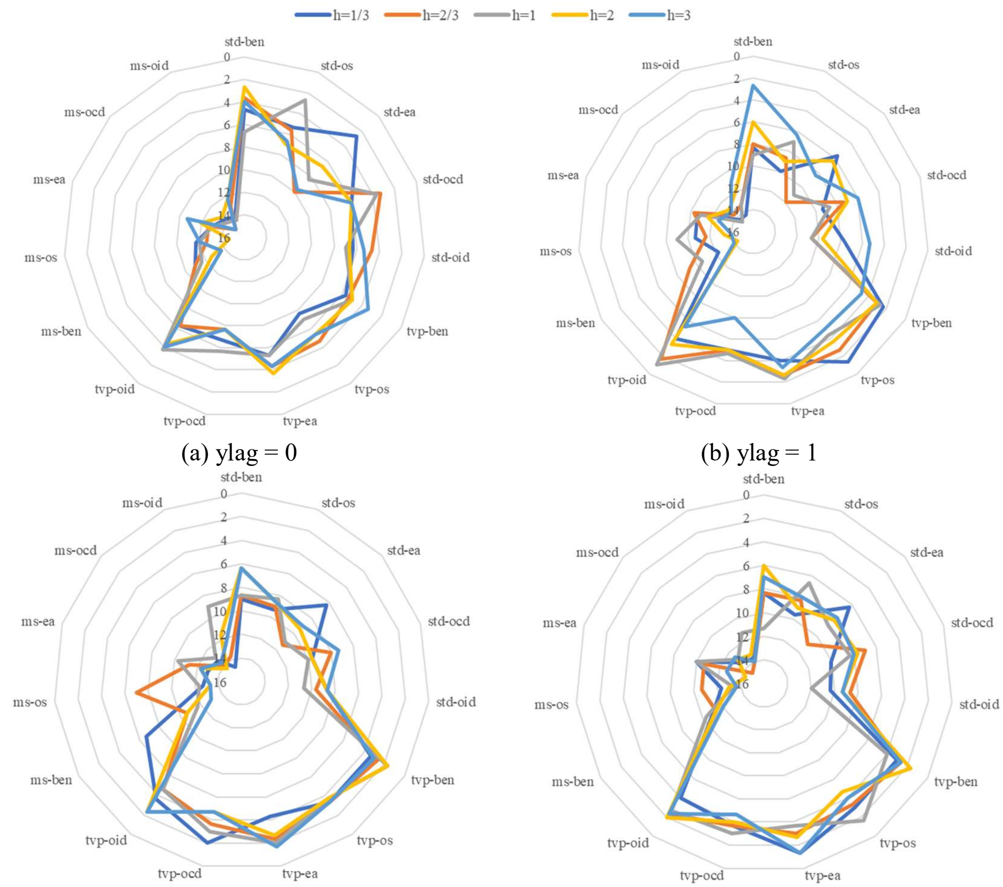
Table 5 Summary of out-of-sample forecast performance (continued)

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=1	MSE	ylag = 0	2.0194	**1.9389**	2.0624	1.9419	2.0257	3.3502	3.7033	4.0524	5.2612	4.5138	1.9945	1.9971	1.9945	1.9978	1.9921
		ylag = 1	4.0159	3.8161	4.0176	3.8397	4.0315	2.6663	2.2351	3.6747	7.9248	3.9707	2.0484	2.0555	2.0489	2.0574	**2.0480**
		ylag = 2	4.3336	4.0563	4.3370	4.1875	4.3555	2.9428	4.0911	2.3012	14.2250	2.3968	2.0613	2.0637	**2.0595**	2.0767	2.0651
		ylag = 3	4.7889	4.4714	4.7880	4.6054	4.8075	4.2848	8.1582	3.3200	7.4414	4.9149	2.0646	2.0633	2.0658	2.0682	**2.0619**
	MAE	ylag = 0	0.5996	**0.5936**	0.6086	0.5948	0.5983	1.2704	1.4131	1.3963	1.4907	1.4370	0.6208	0.6218	0.6208	0.6217	0.6189
		ylag = 1	0.6869	0.6694	0.6896	0.6770	0.6902	0.8338	0.7892	0.9060	1.3325	1.0129	0.6085	0.6130	0.6085	0.6108	**0.6074**
		ylag = 2	0.7206	0.6989	0.7232	0.7141	0.7236	0.8156	0.9944	0.7736	1.4989	0.8200	0.6094	0.6134	**0.6092**	0.6099	0.6135
		ylag = 3	0.7579	0.7305	0.7604	0.7479	0.7610	0.9737	1.3788	0.9588	1.4128	1.1337	0.6175	**0.6140**	0.6166	0.6156	0.6151
	MAPE	ylag = 0	1.6664	1.2484	2.3187	1.5507	1.8749	6.7826	2.7518	10.1751	4.8578	13.7198	0.8100	0.8293	0.8099	**0.7995**	0.8009
		ylag = 1	2.0519	2.0367	3.3222	2.3395	2.1572	4.0691	3.2154	3.5829	4.2512	5.6451	0.8247	0.8301	0.8246	0.8349	**0.8145**
		ylag = 2	2.0138	2.9439	3.2783	3.5447	2.6419	16.7471	5.3755	6.7769	2.8769	2.4980	0.7908	0.7927	0.7909	**0.7776**	0.8019
		ylag = 3	9.4623	1.7389	1.8737	2.3096	8.9562	3.0735	2.6331	3.7165	2.3642	1.9868	0.8247	0.8150	0.8233	**0.8109**	0.8302
h=2	MSE	ylag = 0	**1.9950**	2.0171	2.0055	2.0043	1.9995	4.1639	6.2194	3.5275	5.5419	3.8365	1.9993	1.9993	1.9991	2.0046	2.0025
		ylag = 1	2.1041	2.1399	2.1175	2.1127	2.1136	6.2016	4.2254	2.8890	6.5967	2.9635	2.0505	**2.0504**	2.0510	2.0583	2.0942
		ylag = 2	2.2085	2.2676	2.2199	2.2207	2.2282	3.0451	6.2788	7.1114	5.4612	3.3437	2.0588	2.0589	**2.0570**	2.0730	2.0768
		ylag = 3	2.3744	2.4536	2.3836	2.3889	2.3919	3.9360	4.9275	5.0002	4.7661	4.2591	**2.0582**	2.0925	2.0610	2.0730	2.0781
	MAE	ylag = 0	**0.5991**	0.6040	0.6025	0.6030	0.6070	1.4297	1.4852	1.4014	1.7918	1.3862	0.6250	0.6252	0.6249	0.6271	0.6214
		ylag = 1	0.6027	0.6117	0.6040	0.6067	0.6133	1.0230	0.9508	0.8997	1.3254	0.8487	0.6059	0.6067	0.6059	0.6061	**0.6008**
		ylag = 2	0.6198	0.6305	0.6214	0.6250	0.6304	0.9020	1.2236	1.1184	1.4236	0.9279	0.6045	0.6056	0.6052	0.6113	**0.5952**
		ylag = 3	0.6499	0.6654	0.6520	0.6504	0.6614	1.0097	1.0450	1.1914	1.2946	1.1486	0.6058	0.6098	0.6063	0.6096	**0.5967**
	MAPE	ylag = 0	1.2452	1.2454	1.2841	1.2727	1.3217	3.3523	18.2763	4.2584	2.8327	6.8968	0.8190	0.8240	0.8189	0.8295	**0.8126**
		ylag = 1	2.1775	2.1102	2.0567	1.8700	2.2260	12.4362	4.6480	2.5062	2.1208	2.8056	0.8293	0.8302	**0.8291**	0.8428	0.8377
		ylag = 2	1.7771	1.7621	6.6667	5.9721	2.3715	2.8090	5.3009	2.7377	7.7368	3.1493	0.8085	0.8102	0.8095	0.8287	**0.7993**
		ylag = 3	1.3746	1.3888	1.4994	1.3938	1.8331	3.4555	3.4669	6.3313	2.8572	6.8783	0.8148	0.8189	0.8154	0.8297	**0.8058**

Table 5 Summary of out-of-sample forecast performance (continued)

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=3	MSE	ylag = 0	1.9967	2.0028	2.0175	2.0045	2.0006	19.9106	4.6328	4.5056	20.1521	4.5359	1.9954	1.9960	1.9955	2.0053	**1.9879**
		ylag = 1	**2.0468**	2.0539	2.0670	2.0560	2.0524	17.3122	13.1989	12.5936	12.8842	7.1683	2.0519	2.0519	2.0517	2.0599	2.0529
		ylag = 2	2.2071	2.2167	2.2158	2.2188	2.2255	6.2160	7.8673	3.1299	30.0161	4.3013	2.0604	**2.0594**	2.0598	2.0963	2.0602
		ylag = 3	2.2554	2.2658	2.2574	2.2705	2.2700	3.0963	6.5784	3.3086	4.2670	8.7619	2.0628	2.0619	**2.0603**	2.0967	2.0606
	MAE	ylag = 0	**0.5975**	0.6021	0.6045	0.5999	0.5999	1.7032	1.4484	1.4056	2.1614	1.4737	0.6209	0.6223	0.6209	0.6282	0.6195
		ylag = 1	**0.6014**	0.6057	0.6071	0.6034	0.6065	3.4619	2.9796	1.5869	1.7006	1.4920	0.6094	0.6103	0.6094	0.6183	0.6087
		ylag = 2	0.6277	0.6337	0.6345	0.6300	0.6334	1.1890	1.3477	1.0202	2.4009	1.1999	0.6095	0.6104	0.6091	0.6146	**0.6076**
		ylag = 3	0.6376	0.6410	0.6474	0.6400	0.6433	1.0376	1.2564	1.0207	1.2820	1.2999	0.6125	0.6136	**0.6115**	0.6191	0.6119
	MAPE	ylag = 0	1.1869	1.2271	19.5955	1.1916	1.1973	7.7345	5.1409	4.3067	32.9718	5.9846	**0.8095**	0.8163	0.8095	0.8166	0.8271
		ylag = 1	1.2313	1.3089	2.0111	1.3005	1.2570	2.6000	3.6197	2.8709	4.1259	2.0881	0.8138	0.8212	**0.8138**	0.8347	0.8214
		ylag = 2	1.1396	1.1461	1.3426	1.1328	1.1408	4.9132	3.4766	5.1166	3.3507	3.6668	0.7910	0.8019	**0.7907**	0.7976	0.7913
		ylag = 3	1.2049	1.1951	1.1872	1.1915	1.3920	5.4355	7.8434	10.5020	2.6939	3.3796	**0.8052**	0.8163	0.8116	0.8156	0.8142

Note: the grey shadowed result means the model outperforms the benchmark, the bold result represents the best performance under the empirical setting.



(a) ylag = 0 (b) ylag = 1

(c) ylag = 2 (d) ylag = 3

Figure 4 Average ranking of models in out-of-sample forecast

Note: the figure above shows the average ranking across the three measurements (MSE, MAE and MAPE), the smaller ranking i.e. the results that are closer to the outside circle. represents better comprehensive performance).

Table 6 Relative forecast accuracy of single MIDAS models and the DMA models

			std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			OS	EA	OCD	OID	**DMA**	OS	EA	OCD	OID	**DMA**	OS	EA	OCD	OID	**DMA**
h = 1/3	MSE	ylag = 0	1.0105	**0.7957**	1.0115	0.9874	0.9879	0.8692	1.3941	4.7635	1.5951	**0.8241**	1.0105	**0.7957**	1.0115	0.9874	0.9879
		ylag = 1	1.0360	**0.7441**	1.0179	1.0005	0.9597	**0.4465**	0.4630	5.2051	1.3335	0.7515	**0.9998**	1.0026	1.0040	1.0054	1.0004
		ylag = 2	1.0362	**0.7930**	1.0190	1.0013	1.0069	3.2552	4.6125	7.2870	18.1084	**1.1618**	0.9954	0.9998	0.9984	0.9990	**0.9927**
		ylag = 3	1.0465	**0.7992**	1.0215	0.9996	0.9949	1.3009	**0.8416**	5.1888	2.3314	1.2748	0.9959	0.9979	0.9987	0.9992	**0.9899**
	MAE	ylag = 0	0.9957	**0.9284**	1.0065	0.9897	0.9938	1.0675	1.0946	2.2711	1.2732	**0.9719**	0.9957	**0.9284**	1.0065	0.9897	0.9938
		ylag = 1	1.0006	**0.9097**	1.0068	0.9932	0.9833	**0.9307**	0.9701	2.3564	1.2900	1.0639	0.9991	1.0068	1.0103	1.0008	**0.9934**
		ylag = 2	1.0027	**0.9286**	1.0059	0.9942	0.9965	1.6413	1.5951	5.2482	2.0756	**1.0853**	1.0026	1.0052	**0.9943**	0.9986	0.9945
		ylag = 3	1.0046	**0.9376**	1.0064	0.9955	0.9875	1.3469	**1.0790**	2.3932	1.3800	1.5674	1.0068	**0.9939**	1.0036	1.0021	0.9978
	MAPE	ylag = 0	1.2973	0.5503	1.2518	2.9098	**0.3823**	1.1805	1.3240	1.0839	1.8131	**0.3510**	1.2973	0.5503	1.2518	2.9098	**0.3823**
		ylag = 1	1.0306	1.4380	0.9947	0.9941	**0.8283**	1.9681	1.3075	1.3125	3.8583	**0.6851**	0.9935	1.0060	1.0103	1.0045	**0.9918**
		ylag = 2	0.9110	**0.7731**	0.9465	0.9676	0.8468	1.1896	1.4372	0.6049	8.8403	**0.3431**	1.0160	1.0136	**1.0009**	1.0204	1.0336
		ylag = 3	1.0004	0.7823	1.0010	3.4354	**0.7769**	0.6157	0.7400	0.5939	0.8110	**0.4909**	1.0055	**0.9903**	1.0124	1.0223	1.0030
h = 2/3	MSE	ylag = 0	0.9670	1.5869	0.9552	1.0059	**0.9185**	2.8670	1.3313	24.3333	1.9733	**1.3192**	0.9670	1.5869	0.9552	1.0059	**0.9185**
		ylag = 1	0.9627	1.3604	0.9096	1.0041	**0.7633**	2.7163	**0.7741**	5.4646	1.6964	1.1979	0.9988	0.9993	1.0012	**0.9682**	1.0106
		ylag = 2	0.9603	1.3688	0.9081	1.0043	**0.7795**	**0.3379**	0.9797	5.0527	2.5062	1.0770	1.0009	0.9850	**0.9747**	1.0036	1.0101
		ylag = 3	0.9628	1.3695	0.9055	1.0041	**0.7664**	**0.8284**	0.8807	2.7048	2.0056	2.1130	1.0008	0.9987	**0.9860**	1.0007	0.9895
	MAE	ylag = 0	1.0127	1.1044	0.9923	1.0111	**0.9759**	1.5849	**1.1761**	2.8694	1.3750	1.2405	1.0127	1.1044	0.9923	1.0111	**0.9759**
		ylag = 1	0.9947	1.0612	0.9773	1.0058	**0.9419**	1.3236	**0.9844**	2.3720	1.2669	1.0631	0.9979	1.0000	1.0093	**0.9894**	1.0045
		ylag = 2	0.9977	1.0662	0.9744	1.0051	**0.9479**	1.5292	1.1059	8.0177	1.4295	**0.9796**	0.9932	0.9994	1.0000	1.0016	**0.9867**
		ylag = 3	0.9956	1.0720	0.9742	1.0040	**0.9308**	1.0940	**1.0764**	1.9248	1.4708	1.7654	**0.9947**	1.0022	1.0070	0.9965	0.9993
	MAPE	ylag = 0	3.6155	1.8544	1.0412	1.0071	**0.6650**	0.7780	1.4063	2.4005	1.3317	**0.3231**	3.6155	1.8544	1.0412	1.0071	**0.6650**
		ylag = 1	1.2952	1.6809	1.2458	1.6627	**0.4768**	0.9071	1.3638	1.3301	11.2425	**0.4833**	1.0156	**0.9997**	1.0328	1.0028	1.0036
		ylag = 2	1.2098	1.6467	1.0949	1.0564	**0.7678**	0.3906	2.2767	0.9154	2.0600	**0.3775**	1.0210	1.0105	1.0243	1.0152	**1.0087**
		ylag = 3	1.1978	1.2010	1.0901	0.9846	**0.6809**	1.2245	**1.0439**	1.7599	1.8488	1.2370	1.0127	1.0020	1.0285	**0.9929**	1.0110

Table 6 Relative forecast accuracy of single MIDAS models and the DMA (continued)

			std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			OS	EA	OCD	OID	**DMA**	OS	EA	OCD	OID	**DMA**	OS	EA	OCD	OID	**DMA**
h = 1	MSE	ylag = 0	**0.9601**	1.0213	0.9616	1.0031	0.9615	**1.1054**	1.2096	1.5704	1.3473	1.1298	**0.9601**	1.0213	0.9616	1.0031	0.9615
		ylag = 1	0.9503	1.0004	0.9561	1.0039	**0.9488**	**0.8383**	1.3782	2.9723	1.4892	1.3355	1.0034	1.0002	1.0044	0.9998	**0.9944**
		ylag = 2	**0.9360**	1.0008	0.9663	1.0050	0.9421	1.3902	**0.7820**	4.8338	0.8145	0.9221	1.0012	0.9991	1.0075	1.0018	**0.9797**
		ylag = 3	**0.9337**	0.9998	0.9617	1.0039	0.9500	1.9040	**0.7748**	1.7367	1.1471	1.3365	0.9994	1.0006	1.0017	0.9987	**0.9919**
	MAE	ylag = 0	0.9901	1.0150	0.9921	0.9978	**0.9762**	1.1123	1.0991	1.1734	1.1312	**1.0957**	0.9901	1.0150	0.9921	0.9978	**0.9762**
		ylag = 1	0.9745	1.0039	0.9856	1.0047	**0.9706**	**0.9466**	1.0866	1.5980	1.2148	1.1080	1.0074	1.0000	1.0038	0.9982	**0.9923**
		ylag = 2	**0.9699**	1.0036	0.9910	1.0042	0.9818	1.2193	**0.9484**	1.8378	1.0054	1.0206	1.0066	0.9998	1.0008	1.0068	**0.9855**
		ylag = 3	**0.9639**	1.0034	0.9869	1.0041	0.9838	1.4160	**0.9846**	1.4509	1.1642	1.1435	0.9944	0.9985	0.9969	0.9962	**0.9937**
	MAPE	ylag = 0	0.7492	1.3915	0.9306	1.1251	**0.5277**	0.4057	1.5002	0.7162	2.0228	**0.3600**	0.7492	1.3915	0.9306	1.1251	**0.5277**
		ylag = 1	0.9926	1.6191	1.1402	1.0514	**0.4675**	0.7902	0.8805	1.0447	1.3873	**0.3871**	1.0066	1.0000	1.0125	0.9877	**0.9843**
		ylag = 2	1.4619	1.6279	1.7602	1.3119	**0.4947**	0.3210	0.4047	0.1718	0.1492	**0.0764**	1.0024	1.0001	**0.9832**	1.0140	0.9920
		ylag = 3	0.1838	0.1980	0.2441	0.9465	**0.1078**	0.8567	1.2092	0.7692	0.6464	**0.5035**	0.9883	0.9983	**0.9833**	1.0067	0.9936
h = 2	MSE	ylag = 0	1.0111	1.0053	1.0047	**1.0023**	1.0172	1.4937	**0.8472**	1.3309	0.9214	1.1099	1.0111	1.0053	1.0047	**1.0023**	1.0172
		ylag = 1	1.0170	1.0064	**1.0041**	1.0045	2.0031	0.6813	0.4658	1.0637	0.4779	**0.4651**	**0.9999**	1.0002	1.0038	1.0213	1.0051
		ylag = 2	1.0268	**1.0052**	1.0055	1.0090	2.0644	2.0619	2.3354	1.7935	1.0981	**0.9695**	1.0001	0.9992	1.0069	1.0088	**0.9956**
		ylag = 3	1.0333	**1.0039**	1.0061	1.0073	2.0594	1.2519	1.2704	1.2109	**1.0821**	1.1582	1.0167	1.0014	1.0072	1.0097	**0.9992**
	MAE	ylag = 0	1.0082	**1.0056**	1.0065	1.0132	1.0105	1.0388	0.9802	1.2533	**0.9696**	1.0944	1.0082	**1.0056**	1.0065	1.0132	1.0105
		ylag = 1	1.0149	**1.0022**	1.0067	1.0176	1.1639	0.9294	0.8795	1.2956	**0.8296**	8.7914	1.0013	1.0000	1.0003	0.9915	**0.9802**
		ylag = 2	1.0172	**1.0025**	1.0083	1.0170	1.1846	1.3565	1.2399	1.5782	1.0287	**0.9379**	1.0018	1.0012	1.0113	0.9847	**0.9759**
		ylag = 3	1.0238	1.0032	**1.0007**	1.0177	1.1804	**1.0350**	1.1800	1.2822	1.1376	1.0369	1.0067	1.0008	1.0063	**0.9851**	0.9940
	MAPE	ylag = 0	1.0002	1.0312	1.0221	1.0614	**0.7137**	5.4518	1.2703	**0.8450**	2.0573	0.8873	1.0002	1.0312	1.0221	1.0614	**0.7137**
		ylag = 1	0.9691	0.9445	0.8588	1.0222	**0.4469**	0.3737	0.2015	0.1705	0.2256	**0.1287**	1.0011	**0.9998**	1.0162	1.0101	1.0075
		ylag = 2	0.9916	3.7515	3.3606	1.3345	**0.5386**	1.8871	0.9746	2.7543	1.1211	**0.4412**	1.0021	1.0012	1.0249	**0.9886**	1.0086
		ylag = 3	1.0103	1.0908	1.0139	1.3335	**0.6983**	1.0033	1.8322	0.8269	1.9905	**0.4854**	1.0050	1.0007	1.0183	**0.9889**	0.9980

Table 6 Relative forecast accuracy of single MIDAS models and the DMA (continued)

			std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			OS	EA	OCD	OID	**DMA**	OS	EA	OCD	OID	**DMA**	OS	EA	OCD	OID	**DMA**
h = 3	MSE	ylag = 0	1.0031	1.0104	1.0039	1.0019	**0.9862**	0.2327	0.2263	1.0121	0.2278	**0.1859**	1.0031	1.0104	1.0039	1.0019	**0.9862**
		ylag = 1	1.0035	1.0099	1.0045	**1.0027**	1.9390	0.7624	0.7274	0.7442	0.4141	**0.1250**	1.0000	**0.9999**	1.0039	1.0005	1.0062
		ylag = 2	1.0043	**1.0039**	1.0053	1.0083	1.9693	1.2656	**0.5035**	4.8288	0.6920	0.8625	0.9995	0.9997	1.0174	0.9999	**0.9932**
		ylag = 3	1.0046	**1.0009**	1.0067	1.0065	2.0539	2.1246	**1.0685**	1.3781	2.8297	1.7137	0.9996	0.9988	1.0164	0.9989	**0.9958**
	MAE	ylag = 0	1.0077	1.0117	1.0040	1.0040	**1.0011**	0.8504	0.8253	1.2690	0.8653	**0.7375**	1.0077	1.0117	1.0040	1.0040	**1.0011**
		ylag = 1	1.0072	1.0094	**1.0033**	1.0084	1.1275	0.8607	0.4584	0.4912	**0.4310**	0.6169	1.0015	0.9999	1.0147	0.9988	**0.9823**
		ylag = 2	1.0097	1.0110	**1.0037**	1.0091	1.1425	1.1335	**0.8580**	2.0193	1.0092	1.0917	1.0015	0.9994	1.0084	0.9969	**0.9761**
		ylag = 3	1.0054	1.0155	**1.0037**	1.0090	1.1620	1.2109	**0.9837**	1.2356	1.2529	1.1214	1.0017	**0.9983**	1.0107	0.9989	0.9996
	MAPE	ylag = 0	1.0339	16.5102	1.0040	1.0087	**0.7692**	0.6647	0.5568	4.2629	0.7737	**0.2574**	1.0339	16.5102	1.0040	1.0087	**0.7692**
		ylag = 1	1.0630	1.6332	1.0562	1.0209	**0.7773**	1.3922	1.1042	1.5869	**0.8031**	1.2745	1.0091	**1.0000**	1.0257	1.0093	1.0228
		ylag = 2	1.0057	1.1781	0.9940	1.0010	**0.8309**	0.7076	1.0414	0.6820	0.7463	**0.4438**	1.0138	**0.9996**	1.0083	1.0003	1.0117
		ylag = 3	0.9919	0.9853	0.9890	1.1553	**0.7981**	1.4430	1.9321	0.4956	0.6218	**0.3298**	1.0137	**1.0080**	1.0129	1.0111	1.0110

Note: the results are the relative value divided by the metric of benchmark model, hence the value less than 1 (grey shadowed) means the corresponding model outperforms the benchmark. The bold result means the model gains the best accuracy under the empirical setting in corresponding MIDAS structure.

Table 7 Out-of-sample forecast performance of DMA models based on different MIDAS structures

		ylag = 0			ylag = 1			ylag = 2			ylag = 3		
		DMA-std-AR-MIDAS	DMA-MS-AR-MIDAS	DMA-TVP-AR-MIDAS	DMA-std-AR-MIDAS	DMA-MS-AR-MIDAS	DMA-TVP-AR-MIDAS	DMA-std-AR-MIDAS	DMA-MS-AR-MIDAS	DMA-TVP-AR-MIDAS	DMA-std-AR-MIDAS	DMA-MS-AR-MIDAS	DMA-TVP-AR-MIDAS
MSE	h = 1/3	**1.8096**	3.3761	1.9684	2.9127	4.2717	**2.0491**	3.2437	**1.9571**	2.0486	3.4998	3.7399	**2.0433**
	h = 2/3	**1.7924**	3.5571	1.9823	2.8988	3.4811	**2.1178**	3.1511	3.5532	**2.1018**	3.3548	9.9477	**2.0613**
	h = 1	**1.9417**	3.7852	1.9520	3.8102	3.5607	**2.0370**	4.0826	2.7136	**2.0195**	4.5495	5.7265	**2.0480**
	h = 2	2.0292	4.6217	**1.9799**	4.2147	2.8845	**2.0609**	4.5592	2.9522	**2.0497**	4.8900	4.5588	**2.0565**
	h = 3	**1.9691**	3.7008	1.9736	3.9689	2.1642	**2.0647**	4.3464	5.3613	**2.0464**	4.6322	5.3062	**2.0541**
MAE	h = 1/3	**0.5706**	1.0654	0.6162	0.6362	0.9886	**0.6039**	0.6695	0.6989	**0.6057**	0.7021	1.2571	**0.6131**
	h = 2/3	**0.5654**	1.1093	0.6233	0.6361	0.9124	**0.6112**	0.6764	0.7921	**0.6055**	0.7014	1.6265	**0.6144**
	h = 1	**0.5853**	1.3919	0.6135	0.6667	0.9239	**0.6038**	0.7075	0.8324	**0.6005**	0.7456	1.1135	**0.6136**
	h = 2	**0.6054**	1.5646	0.6130	0.7015	8.9936	**0.5939**	0.7343	0.8460	**0.5899**	0.7671	1.0469	**0.6022**
	h = 3	**0.5982**	1.2562	0.6139	0.6781	2.1356	**0.5986**	0.7171	1.2979	**0.5949**	0.7409	1.1636	**0.6123**
MAPE	h = 1/3	0.9294	1.5800	**0.8127**	0.9661	1.6458	**0.8173**	1.0058	1.2146	**0.8077**	1.0021	2.0996	**0.8203**
	h = 2/3	0.9114	1.7837	**0.8207**	0.9880	1.2518	**0.8364**	1.0274	1.0646	**0.8173**	1.0607	2.9600	**0.8279**
	h = 1	0.8794	2.4416	**0.8092**	0.9593	1.5750	**0.8117**	0.9963	1.2797	**0.7845**	1.0200	1.5475	**0.8194**
	h = 2	0.8887	2.9747	**0.8200**	0.9732	1.6008	**0.8355**	0.9572	1.2394	**0.8154**	0.9599	1.6774	**0.8132**
	h = 3	0.9129	1.9911	**0.8217**	0.9572	3.3138	**0.8323**	0.9469	2.1807	**0.8003**	0.9616	1.7926	**0.8141**

Note: the bold result means the model gains the best accuracy across the three DMA models under the empirical setting.

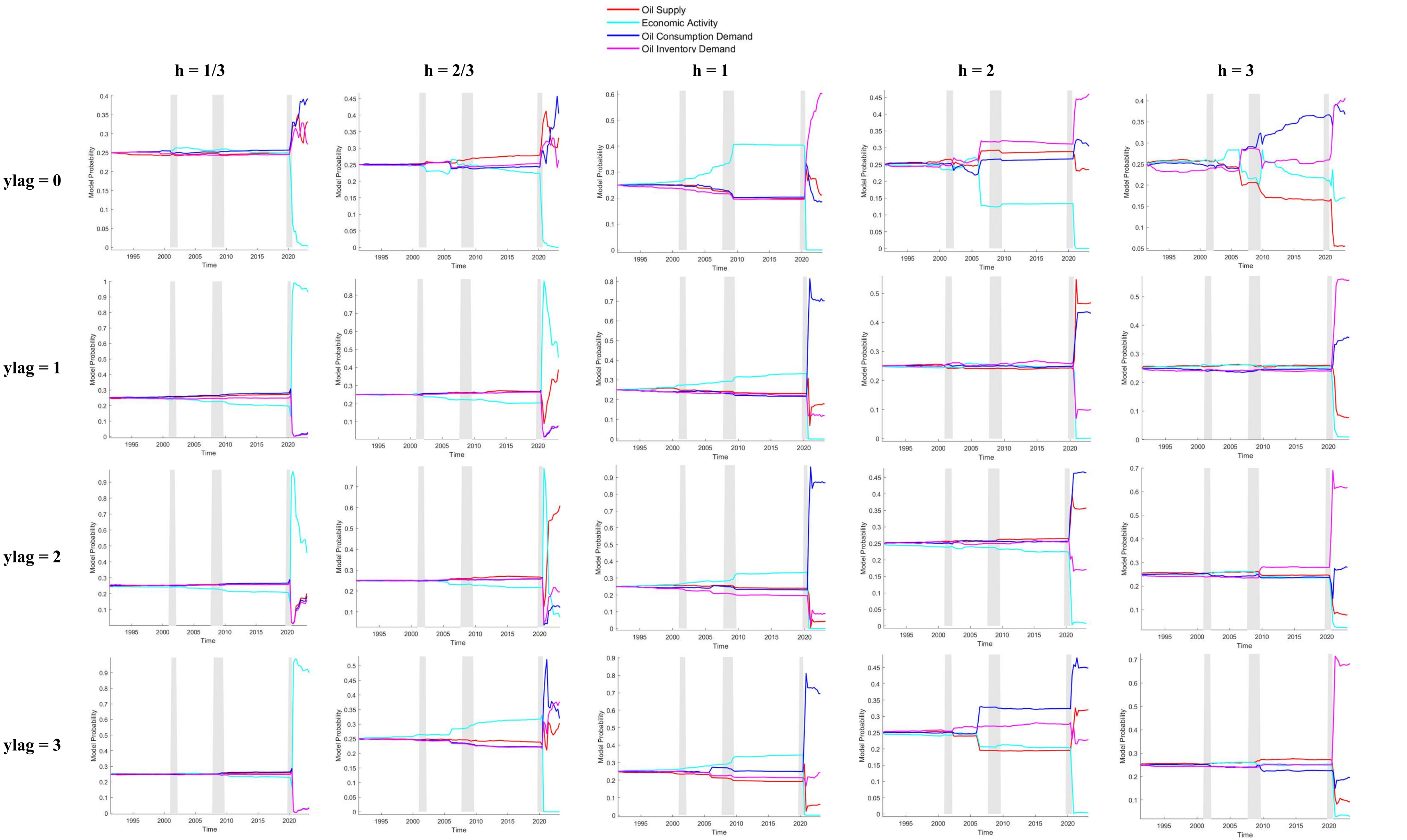


Figure 5 The inclusion probability of sub-model in DMA-std-AR-MIDAS

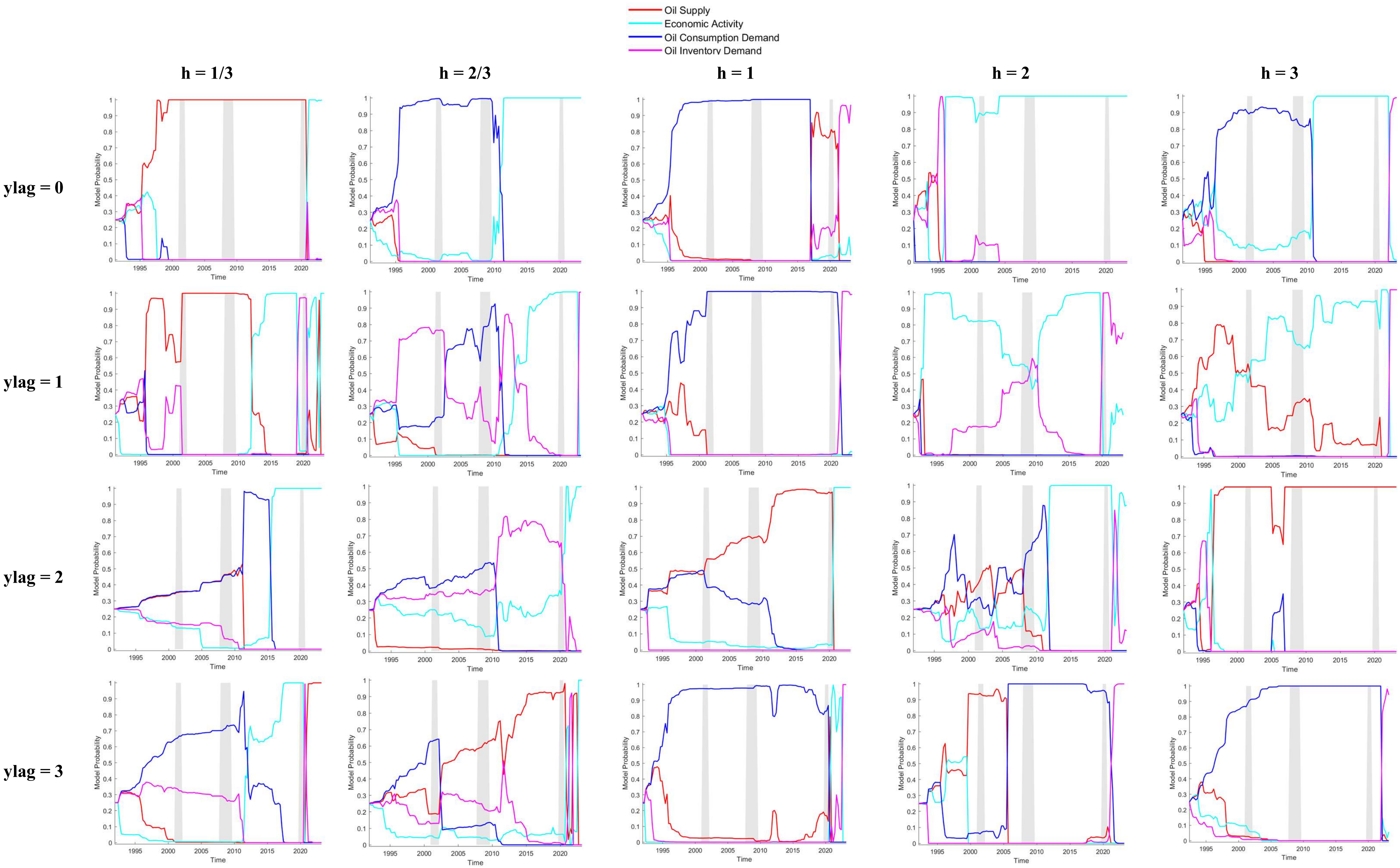


Figure 6 The inclusion probability of sub-model in DMA-MS-AR-MIDAS

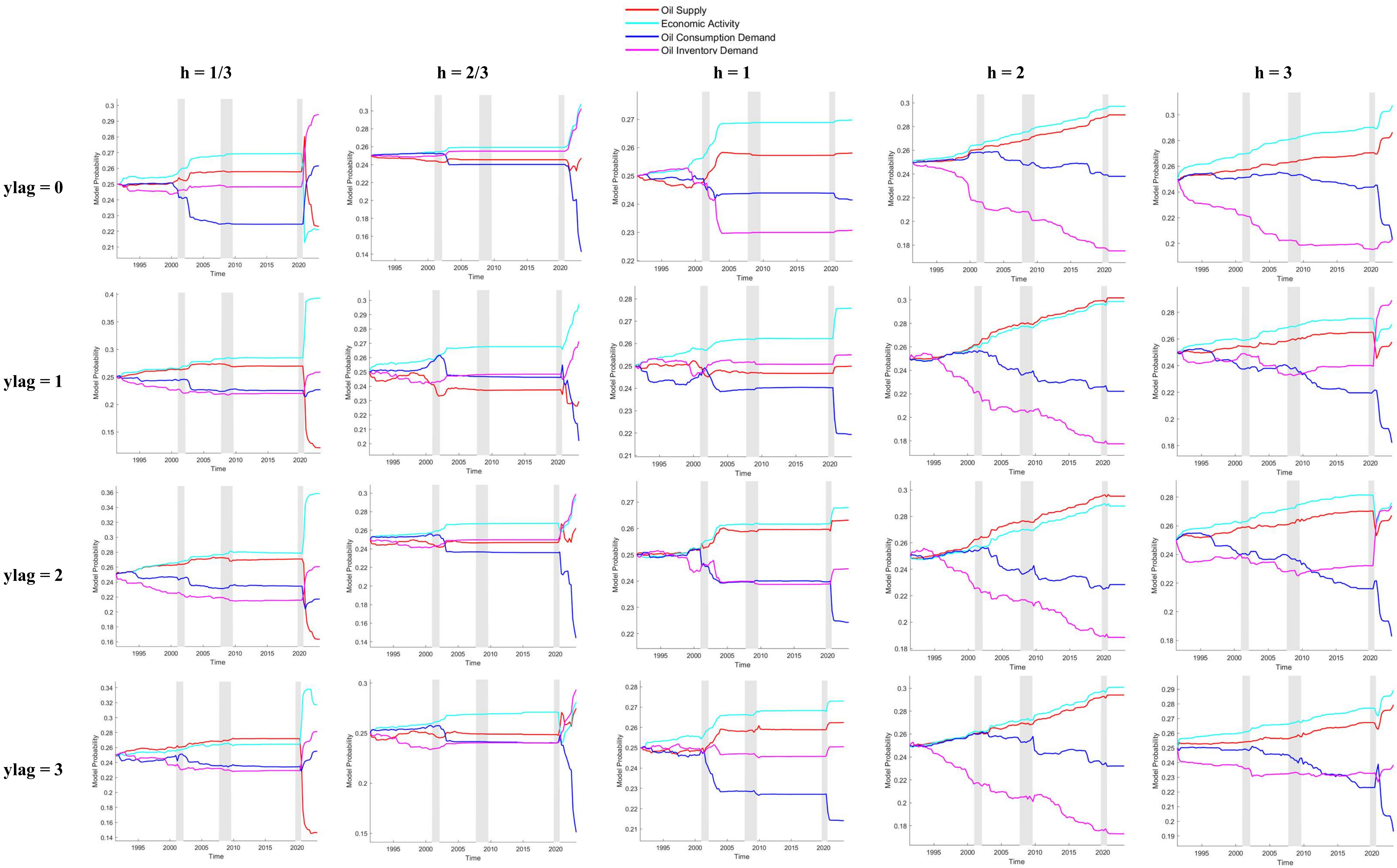


Figure 7 The inclusion probability of sub-model in DMA-TVP-AR-MIDAS

Table 8 Out-of-sample forecast performance of GDP over the World (ex. the US)

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=1/3	MSE	ylag = 0	2.7763	2.7491	**2.2468**	2.7323	2.7223	8.4124	9.0155	8.2165	9.1520	7.2782	2.8777	2.8781	2.8772	2.8759	2.8779
		ylag = 1	7.3409	7.2561	5.6642	7.2113	7.1823	10.1900	10.3046	5.9837	10.6647	6.0744	4.2628	4.2618	4.2631	**4.2589**	4.2628
		ylag = 2	7.3890	7.4695	5.3300	7.4942	7.5426	6.7577	13.7215	14.3639	12.5451	5.1895	4.0944	4.0898	4.0928	**4.0842**	4.0875
		ylag = 3	8.9112	9.1338	6.6129	9.0482	9.0156	4.9946	5.6681	4.5715	6.8270	8.4850	4.0906	**4.0850**	4.0893	4.1069	4.1018
	MAE	ylag = 0	0.6609	0.6612	**0.6222**	0.6643	0.6611	4.5627	4.8866	4.7818	4.6014	4.3145	0.7380	0.7389	0.7364	0.7431	0.7382
		ylag = 1	0.6842	0.6820	0.6318	0.6865	0.6843	1.6203	1.9137	1.2519	1.4455	1.5952	0.6252	0.6262	0.6254	0.6331	**0.6226**
		ylag = 2	0.7323	0.7375	0.6164	0.7397	0.7450	2.5889	1.8661	1.9295	5.3906	1.9412	0.6169	0.6186	0.6170	0.6219	**0.6130**
		ylag = 3	0.8291	0.8434	0.7302	0.8388	0.8409	2.1202	2.9329	3.9567	5.3300	2.0982	0.6182	0.6179	**0.6153**	0.6356	0.6253
	MAPE	ylag = 0	0.8152	0.8181	0.7416	0.8157	0.8049	2.2676	2.7223	2.6696	2.7310	4.7272	0.7218	0.7182	0.7226	0.7443	**0.6986**
		ylag = 1	0.7531	0.7467	0.6749	0.7504	0.7399	3.6838	2.9004	5.5922	6.0701	3.8697	0.6383	0.6410	0.6416	0.6549	**0.6212**
		ylag = 2	0.8121	0.8135	0.7320	0.8174	0.8072	4.7517	7.3471	8.4220	6.8291	4.1348	0.6737	0.6775	0.6738	0.7303	**0.6528**
		ylag = 3	0.8716	0.8769	0.8044	0.8775	0.8681	4.6684	6.8789	4.4399	7.1535	4.1270	0.6777	0.6751	0.6747	0.7398	**0.6651**
h=2/3	MSE	ylag = 0	**2.6567**	2.7640	2.8748	2.8247	2.8435	5.7479	5.5929	6.6554	6.1110	5.2367	2.8875	2.8893	2.8891	2.8927	2.8895
		ylag = 1	7.3330	7.4681	7.2103	7.4413	7.4954	6.2426	7.8052	4.8605	6.2292	8.3607	4.2831	4.2872	4.2844	4.2720	**4.2553**
		ylag = 2	7.2748	7.8853	8.5610	7.7042	7.8000	6.5930	5.8850	4.6130	8.0185	6.9733	4.1608	4.1706	4.1677	**4.1110**	4.1297
		ylag = 3	8.6688	9.5269	9.8543	9.1745	9.2190	6.3763	7.6195	7.9752	7.8455	5.0619	4.1682	4.1757	4.1712	4.1175	**4.0730**
	MAE	ylag = 0	0.6745	**0.6666**	0.7058	0.6724	0.6769	3.3050	4.2645	1.6229	3.5727	1.9080	0.7439	0.7462	0.7454	0.7470	0.7453
		ylag = 1	0.6940	0.6848	0.6974	0.6924	0.6990	2.2530	1.3982	1.2021	1.2498	1.3563	0.6375	0.6398	0.6387	0.6353	**0.6244**
		ylag = 2	0.7254	0.7495	0.7845	0.7461	0.7538	2.8985	1.4364	1.5031	2.9553	3.3991	0.6405	0.6420	0.6416	0.6329	**0.6322**
		ylag = 3	0.8246	0.8514	0.8540	0.8463	0.8486	2.4587	3.1083	2.3213	2.0020	1.7798	0.6420	0.6429	0.6417	0.6364	**0.6149**
	MAPE	ylag = 0	0.8108	0.7917	0.8164	0.8106	0.8179	4.1702	5.8584	5.6390	1.9243	5.1609	0.7217	0.7238	**0.7173**	0.7317	0.7277
		ylag = 1	0.7477	0.7350	0.7294	0.7528	0.7624	3.4665	4.2079	2.5530	5.2239	6.6550	0.6495	0.6520	0.6487	0.6524	**0.6361**
		ylag = 2	0.7981	0.8102	0.7930	0.8170	0.8264	6.4805	3.3895	3.0841	5.4778	7.3136	0.6907	0.6864	0.6818	0.6882	**0.6817**
		ylag = 3	0.8557	0.8732	0.8333	0.8848	0.8810	5.4214	3.6334	6.1880	2.6583	4.3435	0.6928	0.6881	0.6830	0.6962	**0.6733**

Table 8 Out-of-sample forecast performance of GDP over the World (ex. the US) (continued)

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=1	MSE	ylag = 0	2.8516	**2.7658**	2.8250	4.2287	2.8558	5.5062	4.7261	5.5229	5.1992	4.6585	2.8775	2.8867	2.8805	2.8855	2.8826
		ylag = 1	7.4006	7.3558	7.2778	7.4207	7.3617	6.5452	8.9270	4.5386	5.1842	5.8416	4.2589	4.2687	**4.2587**	4.2641	4.3051
		ylag = 2	8.2052	8.1868	7.8326	8.3770	8.1471	8.2453	8.6284	9.5237	9.5501	7.6246	**4.0731**	4.0822	4.0780	4.0992	4.1207
		ylag = 3	11.0861	10.5351	9.8278	11.3656	11.0369	9.4153	9.8621	10.2493	9.4639	9.4413	4.0816	**4.0792**	4.1039	4.0864	4.1392
	MAE	ylag = 0	**0.6656**	0.6761	0.6735	0.7158	0.6679	1.1938	2.5621	3.0718	1.8431	3.1525	0.7393	0.7396	0.7412	0.7459	0.7424
		ylag = 1	0.6758	0.6665	0.6776	0.6737	0.6744	1.3507	1.4247	1.1321	1.2389	2.6652	0.6262	**0.6244**	0.6260	0.6328	0.6249
		ylag = 2	0.7688	0.7561	0.7453	0.7739	0.7655	2.0131	6.4425	3.9484	2.2129	1.7934	0.6161	0.6176	0.6185	0.6240	**0.6159**
		ylag = 3	0.9104	0.8823	0.8629	0.9188	0.9065	1.5963	2.4469	2.3667	1.8380	2.0611	**0.6186**	0.6241	0.6276	0.6231	0.6300
	MAPE	ylag = 0	0.7189	0.7405	0.7361	0.7216	0.7272	5.5634	5.6830	2.1832	2.9597	3.6701	0.7222	**0.7157**	0.7165	0.7360	0.7207
		ylag = 1	0.6590	0.6740	0.6775	0.6609	0.6612	4.7876	3.4450	4.4780	6.1470	4.3101	0.6373	**0.6308**	0.6359	0.6544	0.6439
		ylag = 2	0.7365	0.7347	0.7236	0.7347	0.7364	8.4259	6.7193	4.1041	3.4030	2.1609	0.6738	**0.6536**	0.6708	0.6843	0.6570
		ylag = 3	0.8291	0.8149	0.8012	0.8443	0.8259	5.4158	3.6732	2.7960	6.2604	3.4177	0.6656	**0.6597**	0.6683	0.6843	0.6706
h=2	MSE	ylag = 0	2.9555	2.9090	2.8801	**2.8617**	3.0159	4.1518	4.7426	5.3064	4.7738	4.0330	2.8794	2.8807	2.8781	2.9077	2.8824
		ylag = 1	7.5117	7.6006	7.5462	7.4654	7.6263	6.9090	7.3895	5.1818	8.4606	5.5164	4.2741	**4.2562**	4.2703	4.2720	4.2852
		ylag = 2	8.3787	8.3424	8.2806	8.9496	8.4454	7.8136	4.1855	8.2539	9.9686	4.4156	4.0846	4.0845	4.0864	4.0876	**4.0842**
		ylag = 3	11.1421	11.3443	10.9780	11.2932	11.0517	10.1314	9.6811	10.7270	9.9803	9.7134	**4.0831**	4.0861	4.0872	4.0915	4.1147
	MAE	ylag = 0	0.7030	0.6681	**0.6666**	0.6715	0.7027	3.6650	5.5699	5.5183	4.5457	5.8406	0.7386	0.7425	0.7388	0.7456	0.7419
		ylag = 1	0.7079	0.6872	0.6838	0.6786	0.7139	2.3997	2.6789	1.8445	2.8290	4.4282	0.6267	0.6218	0.6251	0.6276	**0.6200**
		ylag = 2	0.7856	0.7709	0.7703	0.7838	0.7863	2.6406	2.1942	2.1733	1.8348	3.4389	0.6138	0.6125	0.6148	0.6211	**0.6101**
		ylag = 3	0.9158	0.9187	0.9115	0.9046	0.9116	2.9225	4.4157	5.1020	1.1312	6.1215	0.6152	**0.6140**	0.6162	0.6230	0.6141
	MAPE	ylag = 0	0.7403	0.7198	**0.7070**	0.7561	0.7427	2.2273	2.5991	7.3574	4.4066	5.7170	0.7337	0.7560	0.7193	0.7399	0.7346
		ylag = 1	0.6838	0.6672	0.6564	0.7085	0.6842	5.1556	2.0693	13.6120	3.3758	4.8953	0.6536	**0.6296**	0.6421	0.6406	0.6375
		ylag = 2	0.7476	0.7454	0.7273	0.7643	0.7437	13.7640	8.5106	7.4269	8.0296	9.7947	0.6775	0.6716	0.6749	0.6905	**0.6585**
		ylag = 3	0.8298	0.8455	0.8207	0.8422	0.8235	4.5664	3.0465	7.6736	6.3977	4.3437	0.6803	0.6753	0.6770	0.6918	**0.6633**

Table 8 Out-of-sample forecast performance of GDP over the World (ex. the US) (continued)

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=3	MSE	ylag = 0	2.8229	2.8310	2.8182	2.8339	**2.7988**	8.4956	8.1273	8.5853	9.0482	9.4233	2.9313	2.8972	2.9015	2.8167	2.8342
		ylag = 1	7.3502	7.3681	7.3645	7.4103	7.2864	7.7585	8.9854	8.8347	9.9216	7.4193	4.2508	4.2179	4.2509	**4.1730**	4.2183
		ylag = 2	8.0656	8.0355	8.4980	8.3381	8.0725	15.8098	11.1680	9.4921	17.1996	12.0378	4.0689	4.0475	4.0673	4.0312	**4.0121**
		ylag = 3	10.7195	10.4452	11.6733	11.2121	11.1554	12.9118	12.9508	12.3558	9.0216	6.8777	4.0623	**4.0446**	4.0705	4.0837	4.0526
	MAE	ylag = 0	0.6651	0.6794	0.6734	0.6707	**0.6637**	2.4369	1.4002	1.3889	2.3875	1.8067	0.7548	0.7526	0.7482	0.7445	0.7229
		ylag = 1	0.6672	0.6810	0.6740	0.6753	0.6635	5.2195	9.9519	2.9282	7.7569	2.6790	0.6288	0.6313	0.6291	0.6293	**0.6244**
		ylag = 2	0.7496	0.7544	0.7639	0.7691	0.7531	8.0777	7.6975	7.6861	8.8528	8.4841	0.6157	0.6198	0.6194	0.6253	**0.6108**
		ylag = 3	0.8870	0.8800	0.8987	0.9106	0.9046	16.8067	13.5788	16.9769	15.1604	15.2517	0.6164	0.6212	0.6194	0.6357	**0.6137**
	MAPE	ylag = 0	0.7404	0.7499	0.7478	0.7416	**0.7290**	3.4371	4.8435	3.7927	4.2833	5.9366	0.8381	0.8543	0.7894	0.7894	0.7859
		ylag = 1	0.6807	0.6814	0.6768	0.6720	0.6571	8.8862	4.8947	4.8774	3.7500	3.8361	0.6606	0.6878	0.6598	0.6796	**0.6314**
		ylag = 2	0.7494	0.7262	0.7304	0.7381	0.7240	4.6661	5.4403	7.5354	8.3203	4.6519	0.6955	0.7172	0.6962	0.7286	**0.6552**
		ylag = 3	0.8421	0.8082	0.8168	0.8348	0.8323	9.1708	8.4600	6.5623	88.2011	12.4132	0.6975	0.7222	0.6953	0.7377	**0.6613**

Note: the grey shadowed result means the model outperforms the benchmark, the bold result represents the best performance under the empirical setting.

Table 9 Out-of-sample forecast performance of GDP in the advanced region (ex. the US)

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=1/3	MSE	ylag = 0	2.2974	2.3231	**2.0266**	2.2993	2.2635	2.9496	4.2166	3.7645	3.9058	7.8672	2.2545	2.2545	2.2545	2.2497	2.2559
		ylag = 1	6.9507	7.0799	5.1059	6.2100	6.8972	5.1978	13.3378	3.0210	12.8276	5.4017	**2.8331**	2.8509	2.8425	2.8402	2.8414
		ylag = 2	7.9617	8.0483	6.2166	8.0720	7.9681	2.9582	3.9974	2.9548	4.3849	5.8154	2.8432	2.8549	2.8453	**2.8408**	2.8442
		ylag = 3	8.0656	8.2666	6.6075	8.1777	8.1803	7.1418	7.3806	13.7039	16.5135	6.8226	2.8410	2.8582	2.9057	2.8310	**2.8175**
	MAE	ylag = 0	0.5454	0.5486	**0.5065**	0.5420	0.5372	1.0583	1.1874	1.0448	2.7787	1.4685	0.5310	0.5299	0.5311	0.5359	0.5319
		ylag = 1	0.6721	0.6722	0.6099	0.6603	0.6636	1.1437	1.8691	0.7921	3.7532	1.1702	**0.5111**	0.5116	0.5133	0.5154	0.5113
		ylag = 2	0.7217	0.7227	0.6869	0.7288	0.7249	0.9342	1.6962	0.9441	2.5324	1.2985	0.5143	**0.5141**	0.5164	0.5191	0.5147
		ylag = 3	0.7318	0.7398	0.7252	0.7395	0.7424	1.1534	1.3213	1.3097	1.9580	1.4210	0.5137	**0.5134**	0.5188	0.5185	0.5138
	MAPE	ylag = 0	6.7905	6.5934	6.2995	7.1093	6.5641	4.4574	4.9542	**2.9866**	6.4691	5.4772	4.2844	4.3400	4.2707	3.9081	4.2224
		ylag = 1	6.7084	6.7077	6.4124	6.9739	6.6214	2.7299	**2.1908**	3.3789	3.4458	2.4775	3.8471	3.8014	3.7634	3.7861	3.7721
		ylag = 2	6.9329	6.7497	6.4920	7.0331	6.7356	4.1296	5.5132	10.0902	**2.7276**	3.2360	4.0105	3.9572	3.9070	3.9222	3.8966
		ylag = 3	6.7879	6.7063	6.4820	6.9475	6.6892	5.2529	3.8114	**1.8777**	9.5089	2.4248	3.9647	3.9146	3.8823	3.8631	3.8735
h=2/3	MSE	ylag = 0	2.3678	2.3790	2.2919	2.3814	**2.2287**	3.0375	10.5265	3.4707	4.2205	4.6744	2.2545	2.2552	2.2544	2.2572	2.2558
		ylag = 1	7.1517	7.4084	5.0017	7.3018	6.8430	4.5840	6.9600	4.3526	5.1631	7.1834	2.8415	**2.8388**	2.8415	2.8430	2.8426
		ylag = 2	8.0359	8.4510	5.7029	8.3523	7.9591	5.6444	5.2420	5.5891	22.1291	24.8834	**2.8427**	2.8435	2.8437	2.8455	2.8454
		ylag = 3	8.2218	8.3630	6.9084	8.4766	8.2659	5.4119	6.9826	5.7842	12.6395	10.1430	2.8435	**2.8412**	2.8471	2.8457	2.8424
	MAE	ylag = 0	0.5581	0.5499	0.5500	0.5580	0.5384	1.0215	1.5407	0.9823	2.5613	2.1447	0.5310	0.5320	**0.5308**	0.5322	0.5322
		ylag = 1	0.6814	0.6774	0.6082	0.6804	0.6534	1.0207	1.9674	1.0263	3.2566	1.3660	0.5125	0.5128	0.5128	0.5147	**0.5115**
		ylag = 2	0.7279	0.7360	0.6786	0.7352	0.7152	0.9572	1.1803	1.1181	2.4160	1.5163	0.5152	0.5161	0.5145	0.5185	**0.5141**
		ylag = 3	0.7420	0.7356	0.7394	0.7452	0.7363	1.0900	1.2798	1.1010	4.1432	1.5760	0.5156	0.5169	0.5158	0.5183	**0.5143**
	MAPE	ylag = 0	6.5857	5.9930	5.7109	6.0291	5.7866	6.2541	8.2168	8.2353	6.1796	13.2866	4.2846	4.3140	**4.2841**	4.3380	4.3331
		ylag = 1	6.6928	6.0206	5.2983	6.0490	5.8832	6.0691	2.9379	2.8129	**1.6734**	2.8348	3.8769	3.8373	3.8755	3.9222	3.9784
		ylag = 2	6.7700	6.1287	5.8030	6.2242	6.0060	5.3897	3.1682	**2.7877**	3.5366	4.6814	4.0214	3.9789	4.0117	4.0658	4.0826
		ylag = 3	6.7592	6.0958	5.7486	6.1384	5.9599	4.3122	2.0238	2.0345	**1.2095**	3.7222	4.0106	3.9678	4.0013	4.0519	4.0750

Table 9 Out-of-sample forecast performance of GDP in the advanced region (ex. the US) (continued)

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=1	MSE	ylag = 0	2.3067	**2.2394**	2.2550	3.5649	2.2975	5.0629	4.0793	2.6406	9.8301	3.5357	2.2545	2.2653	2.2531	2.2566	2.2555
		ylag = 1	7.5503	7.3644	7.3831	7.8124	7.5548	3.3995	3.6369	2.9070	53.1701	5.0275	2.8423	2.9026	**2.8373**	2.8454	2.8788
		ylag = 2	8.5792	8.3314	8.4308	8.9322	8.5400	2.9918	19.6186	3.8745	17.8140	2.8754	**2.6255**	2.8480	2.8428	2.8635	2.8833
		ylag = 3	8.7607	8.4746	8.4754	9.2225	8.7063	4.4488	6.1401	5.0198	3.8456	3.5667	2.8450	**2.8396**	2.8404	2.8430	2.8645
	MAE	ylag = 0	0.5204	0.5133	0.5322	0.5974	**0.5076**	1.2500	1.2223	0.9948	1.9443	1.2800	0.5310	0.5309	0.5287	0.5342	0.5329
		ylag = 1	0.6442	0.6280	0.6532	0.6569	0.6424	0.8627	0.9379	0.8035	2.8660	1.1211	0.5119	0.5196	0.5112	0.5157	**0.5108**
		ylag = 2	0.7114	0.6764	0.7050	0.7167	0.7049	0.8724	1.4146	0.9415	2.0816	0.9962	**0.5061**	0.5117	0.5150	0.5204	0.5156
		ylag = 3	0.7262	0.6940	0.7127	0.7441	0.7242	0.9627	1.1620	0.9465	2.5567	1.1471	0.5142	**0.5118**	0.5146	0.5170	0.5146
	MAPE	ylag = 0	5.3053	5.5788	4.8107	5.2256	5.1297	5.2551	10.1582	**3.3411**	3.3632	3.6223	4.2844	4.2172	4.2426	4.4167	4.4200
		ylag = 1	5.1935	5.1347	5.2125	4.8399	5.1923	3.6138	2.1682	5.2480	**1.2326**	2.0377	3.8463	4.5946	3.8433	4.1226	4.0041
		ylag = 2	5.3525	5.3595	5.3586	4.9293	5.3497	5.4925	**1.8976**	6.4820	2.6990	3.5835	4.0083	4.0118	3.9973	4.2726	4.1736
		ylag = 3	5.2803	5.2935	5.3056	4.8624	5.2996	4.8637	4.4641	4.7336	**2.6559**	4.7794	3.9721	4.6627	3.9351	4.2903	4.1601
h=2	MSE	ylag = 0	2.2740	2.3395	2.2771	**2.2395**	2.3423	3.8742	5.3468	4.1624	13.5232	6.3649	2.2545	2.2616	2.2546	2.2606	2.2550
		ylag = 1	7.4347	7.5477	7.4186	7.6280	7.4425	7.3993	4.9318	8.1116	12.8748	8.9754	2.8400	2.8404	2.8412	**2.8305**	2.8476
		ylag = 2	8.8833	8.9405	8.6669	8.9754	8.8342	7.8178	6.6680	5.4120	7.9531	7.8719	2.8431	**2.8249**	2.8429	2.8407	2.8700
		ylag = 3	8.9887	9.1482	8.8162	9.0951	9.0271	8.1718	10.1745	7.4644	10.5615	8.6332	2.8424	**2.8035**	2.8413	2.8456	2.8687
	MAE	ylag = 0	0.5474	0.5460	**0.5217**	0.5284	0.5498	1.2814	1.3942	1.2617	2.0284	1.4888	0.5311	0.5318	0.5312	0.5357	0.5310
		ylag = 1	0.6519	0.6551	0.6545	0.6433	0.6719	2.4645	2.5200	1.6079	4.3798	2.9323	0.5124	**0.5084**	0.5138	0.5196	0.5103
		ylag = 2	0.7314	0.7249	0.7203	0.6965	0.7468	3.7006	3.2333	1.2271	4.7769	2.1956	0.5146	**0.5107**	0.5152	0.5188	0.5133
		ylag = 3	0.7478	0.7436	0.7361	0.7048	0.7586	2.2532	2.2522	1.4235	3.5200	1.6836	0.5142	**0.5090**	0.5154	0.5209	0.5147
	MAPE	ylag = 0	5.3548	5.0067	5.1226	5.3470	5.7521	4.9513	**3.3383**	6.8003	3.7595	3.9127	4.2847	4.4719	4.2940	5.4768	4.2082
		ylag = 1	5.0339	5.0487	5.1596	5.2731	5.1756	3.6912	**1.9740**	2.4923	4.1325	2.8172	3.9220	4.1196	3.9064	3.9890	3.7622
		ylag = 2	5.0343	5.0961	5.1692	5.2882	5.2946	3.5431	5.8270	6.2394	**1.7605**	9.0327	4.0499	4.3169	4.0327	4.0956	3.8408
		ylag = 3	5.0256	5.0431	5.0759	5.1662	5.3377	4.0647	3.0316	**2.7872**	6.7325	3.2645	4.0431	4.2966	4.0348	4.1099	3.8342

Table 9 Out-of-sample forecast performance of GDP in the advanced region (ex. the US) (continued)

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=3	MSE	ylag = 0	2.2848	2.2812	2.2630	2.2548	2.2254	5.1528	18.5295	5.0954	11.7495	4.9311	2.2535	**2.2207**	2.2532	2.2592	2.2329
		ylag = 1	7.3564	7.3375	7.2864	7.2402	7.2533	8.6240	6.7734	**2.2471**	15.0782	11.3856	2.8411	2.7873	2.8211	2.8465	2.8181
		ylag = 2	8.8882	8.9681	8.6812	8.8378	8.8141	7.1837	20.6918	5.5509	428.3992	9.1087	2.8435	**2.7821**	2.8447	2.8475	2.8210
		ylag = 3	9.1226	9.1954	8.7848	9.0549	9.0237	9.0408	12.3012	7.6956	14.6914	5.3690	2.8519	2.8382	2.8455	2.8450	**2.8111**
	MAE	ylag = 0	0.5300	0.5366	0.5324	0.5349	**0.5197**	1.3737	2.0809	1.4397	2.1578	1.4059	0.5300	0.5276	0.5298	0.5330	0.5255
		ylag = 1	0.6489	0.6507	0.6504	0.6502	0.6384	4.2132	3.5578	2.2514	14.3089	1.9451	0.5116	0.5117	0.5109	0.5202	**0.5071**
		ylag = 2	0.7275	0.7304	0.7040	0.7297	0.7229	1.4933	2.3804	1.4577	5.0997	1.6230	0.5147	**0.5105**	0.5145	0.5174	0.5119
		ylag = 3	0.7574	0.7513	0.7129	0.7552	0.7507	1.5156	1.9398	1.6437	2.8176	1.3480	0.5160	0.5137	0.5159	0.5197	**0.5109**
	MAPE	ylag = 0	5.4657	5.1628	5.0945	5.1960	4.9233	**3.2508**	12.3349	5.0413	6.2383	7.0788	4.3436	4.4087	4.3393	5.1883	3.9262
		ylag = 1	4.9091	5.0984	5.0000	5.0314	4.8329	1.9271	2.6323	1.9413	**1.5340**	2.0111	3.9150	3.9495	3.9153	4.3622	3.5852
		ylag = 2	4.9115	5.1170	5.0057	5.0512	4.8587	2.2630	3.1199	4.1621	**2.1329**	7.1906	4.0729	4.0968	4.0729	4.5622	3.6997
		ylag = 3	4.9277	5.0893	4.9551	5.0108	4.8913	2.9075	2.4242	3.4753	**2.1148**	2.6321	4.0397	4.0393	4.0393	4.5613	3.7470

Note: the grey shadowed result means the model outperforms the benchmark, the bold result represents the best performance under the empirical setting.

Table 10 Out-of-sample forecast performance of GDP in the emerging region

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=1/3	MSE	ylag = 0	4.8350	4.8189	**4.4201**	5.0167	4.8168	10.7725	12.7508	7.7816	11.6941	7.7093	5.0802	5.2032	5.3274	5.1766	5.0621
		ylag = 1	6.8959	6.8707	**5.8147**	7.1709	6.8803	9.5037	6.1287	7.1365	16.1996	9.7543	6.7010	6.4212	6.3513	6.3797	6.4694
		ylag = 2	11.6175	11.5929	**5.7517**	11.8240	11.4674	10.8280	11.1929	10.8427	19.9611	11.6377	6.5173	6.4686	6.4609	6.6478	6.4728
		ylag = 3	17.5736	17.6838	10.0132	17.9143	17.5350	8.3740	8.9366	8.2733	8.8242	7.2643	6.7249	6.3251	**6.2767**	6.3780	6.4825
	MAE	ylag = 0	1.0687	**1.0580**	1.0792	1.0824	1.0611	13.2504	13.0016	14.3194	6.2100	12.1106	1.2190	1.2709	1.2957	1.2263	1.2098
		ylag = 1	0.8850	**0.8763**	0.9067	0.8958	0.8776	2.8023	9.4677	6.1394	6.3623	3.2690	0.9571	0.9283	0.9133	0.9090	0.9356
		ylag = 2	1.1282	1.1253	0.9762	1.1437	1.1104	3.8774	5.5979	5.8093	5.9607	9.0777	0.9015	0.9051	0.9051	0.9411	**0.8985**
		ylag = 3	1.2954	1.2965	1.1111	1.3030	1.2710	4.1226	4.9687	3.9073	4.7322	5.3790	0.9585	0.9334	**0.9145**	0.9388	0.9510
	MAPE	ylag = 0	0.7765	**0.7632**	0.7695	0.8084	0.7735	7.4121	4.6335	6.4770	4.1735	5.0291	0.8760	0.8538	0.8531	0.8966	0.8031
		ylag = 1	0.6264	**0.6137**	0.6196	0.6436	0.6230	5.3136	11.8224	7.2927	10.8243	6.7539	0.7722	0.6974	0.6607	0.7086	0.6924
		ylag = 2	0.7103	0.6998	0.6918	0.7267	0.6984	4.4220	3.2004	8.5112	5.0959	2.9083	0.7285	0.6924	**0.6686**	0.7411	0.6750
		ylag = 3	0.8244	0.8159	0.7824	0.8280	0.8146	4.0427	2.7108	4.9758	6.1648	2.4088	0.7901	0.7490	**0.6816**	0.8277	0.7344
h=2/3	MSE	ylag = 0	4.9312	5.0360	**3.5736**	4.9110	4.8765	11.8297	11.5761	9.2027	13.5552	12.5790	5.2243	5.2016	5.2042	5.2072	5.0863
		ylag = 1	7.1981	7.5940	6.4920	7.5392	7.2479	7.7238	7.0542	7.8841	8.8219	6.4354	6.3435	**6.3194**	6.3432	6.3575	6.3562
		ylag = 2	11.9053	10.6006	6.5456	11.0376	10.5705	6.7492	**5.4361**	6.8280	10.1215	7.0249	6.4806	6.4741	6.4775	6.5064	6.4377
		ylag = 3	18.1979	16.7630	11.6743	17.0607	16.8319	7.5092	8.2155	8.8938	9.0561	7.1056	6.2929	6.3461	6.3312	6.4101	**6.2696**
	MAE	ylag = 0	1.0498	1.0504	**0.9784**	1.0532	1.0275	6.8268	6.0997	12.2217	5.2417	6.4531	1.2392	1.2772	1.2764	1.2733	1.2778
		ylag = 1	**0.8674**	0.8935	0.8797	0.8935	0.8689	7.0066	8.8060	6.1928	6.2064	3.0589	0.9045	0.8970	0.9086	0.9107	0.9023
		ylag = 2	1.1089	1.0940	0.9826	1.0998	1.0700	4.1656	2.7492	6.8923	5.9331	7.2778	0.8984	0.8978	0.9039	0.8976	**0.8914**
		ylag = 3	1.2765	1.2614	1.1236	1.2666	1.2350	7.3491	8.3850	7.6326	11.4025	13.2966	**0.9129**	0.9170	0.9254	0.9455	0.9211
	MAPE	ylag = 0	0.7480	0.7553	0.8428	0.7619	0.7305	10.7489	11.3845	6.8817	10.5580	8.1928	0.8403	0.8614	**0.7196**	0.9016	0.8966
		ylag = 1	0.6085	0.6143	**0.5765**	0.6241	0.6010	4.8828	10.3107	4.0117	3.8095	6.2919	0.6762	0.6757	0.6622	0.7187	0.6998
		ylag = 2	0.6903	0.6945	0.6731	0.7123	0.6699	3.6986	8.8055	3.6915	5.6674	4.6722	0.6828	0.6853	**0.6565**	0.6935	0.7190
		ylag = 3	0.8077	0.8094	0.7583	0.8250	0.7817	3.1085	10.1626	3.3251	8.1547	2.5213	0.7550	0.7408	**0.7168**	0.8132	0.7815

Table 10 Out-of-sample forecast performance of GDP in the emerging region (continued)

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=1	MSE	ylag = 0	5.1397	5.2330	5.2240	5.2433	5.2337	9.0788	8.2009	8.0429	12.2349	9.6947	4.6786	4.6224	**4.0125**	4.6403	4.5607
		ylag = 1	7.3720	7.1088	6.6318	7.3758	7.1431	11.6327	19.1952	9.5082	13.3530	9.9058	6.3368	**6.3237**	6.3312	6.3280	6.3527
		ylag = 2	9.6555	9.6073	7.1201	9.7520	9.6201	14.9573	14.1474	14.8468	15.0203	14.8358	6.4710	6.4622	6.4613	6.4781	**6.4566**
		ylag = 3	14.4280	14.3640	12.4759	15.1902	14.9068	10.2055	12.1368	11.3515	15.5509	8.8335	6.3093	**6.2796**	6.2828	6.3010	6.2829
	MAE	ylag = 0	1.0488	1.0431	**1.0186**	1.0662	1.0417	4.3290	4.0774	6.7783	4.8906	8.1483	1.2779	1.2366	1.2707	1.2697	1.2740
		ylag = 1	0.8991	**0.8769**	0.8922	0.9119	0.8896	4.3288	3.7644	3.9761	5.0142	2.9005	0.9049	0.9007	0.9067	0.9065	0.9151
		ylag = 2	1.0736	1.0469	0.9905	1.0705	1.0556	2.3202	17.3877	3.6430	12.6818	4.1154	0.9020	**0.8937**	0.9034	0.9038	0.8952
		ylag = 3	1.2380	1.1999	1.1491	1.2366	1.2165	4.7982	5.9682	5.5467	9.5717	5.1153	0.9311	0.9170	0.9176	0.9266	**0.9097**
	MAPE	ylag = 0	0.7933	0.7693	**0.7349**	0.8097	0.7811	4.8095	4.0326	4.6268	6.4352	6.6503	0.8660	0.8342	0.8398	0.8703	0.8508
		ylag = 1	0.6494	0.6274	**0.6032**	0.6578	0.6389	12.4499	11.3244	9.9854	13.1426	11.2636	0.6771	0.6660	0.6623	0.6735	0.6750
		ylag = 2	0.7253	0.6992	0.6654	0.7243	0.7050	2.9024	2.5081	12.2405	4.8415	5.0514	0.6846	0.6777	0.6718	0.6937	**0.6646**
		ylag = 3	0.8341	0.8009	0.7673	0.8309	0.8073	3.2527	3.2796	13.6329	5.2019	3.5712	0.7857	0.7682	**0.7068**	0.7695	0.7136
h=2	MSE	ylag = 0	5.0358	**4.9388**	6.5853	5.0359	5.0529	8.5455	5.8798	8.7823	6.6709	7.0154	5.2715	5.2591	5.2784	5.2576	5.2832
		ylag = 1	6.8934	6.6531	7.0936	6.8410	6.8927	10.8914	12.2068	8.8559	13.6161	11.5764	6.3097	**6.3065**	6.3174	6.3261	6.3203
		ylag = 2	10.3628	8.5407	12.1062	9.5093	10.4050	12.3454	11.6724	12.5897	20.8221	13.9431	6.4432	**6.4271**	6.4391	6.4434	6.4420
		ylag = 3	16.8878	13.2694	17.2185	16.8729	16.9272	8.8805	8.1562	7.9415	8.4573	7.9084	6.2548	6.2528	6.2668	6.3016	**6.2502**
	MAE	ylag = 0	1.0645	**1.0556**	1.1039	1.0769	1.0673	12.2686	6.2853	11.5184	13.4925	5.7853	1.2656	1.2518	1.2694	1.2563	1.2765
		ylag = 1	0.8745	**0.8320**	0.8634	0.8926	0.8782	7.0718	16.5987	6.4612	21.2318	20.7093	0.8934	0.8959	0.9017	0.8980	0.9066
		ylag = 2	1.0730	0.9886	1.0991	1.0528	1.0769	4.7465	11.1612	7.4205	4.1696	11.7144	0.8908	**0.8885**	0.8950	0.8912	0.8997
		ylag = 3	1.2383	1.1466	1.2734	1.2515	1.2425	4.5862	4.5481	5.8918	5.4243	5.2385	0.9032	**0.8956**	0.9064	0.9074	0.9045
	MAPE	ylag = 0	**0.7254**	0.7258	0.7427	0.7487	0.7281	5.2322	12.1996	10.9233	4.2848	12.8226	0.8244	0.8282	0.8201	0.8382	0.8331
		ylag = 1	0.6102	**0.5757**	0.6332	0.6334	0.6044	3.7548	8.5624	3.1247	3.2114	4.4015	0.6586	0.6536	0.6513	0.6662	0.6630
		ylag = 2	0.6721	0.6691	0.6637	0.6601	0.6915	4.3973	19.3661	7.1547	8.8456	19.6035	0.6715	**0.6256**	0.6833	0.6744	0.6656
		ylag = 3	0.7809	0.7304	0.8047	0.8069	0.7790	3.3540	4.2993	22.6231	4.8409	10.7217	0.7089	**0.6944**	0.6948	0.7078	0.7090

Table 10 Out-of-sample forecast performance of GDP in the emerging region (continued)

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=3	MSE	ylag = 0	4.9295	4.9565	**4.6299**	4.9635	4.9177	7.0725	6.1992	9.3166	9.7038	9.3271	5.2087	5.2229	5.2172	5.2083	5.2190
		ylag = 1	7.0217	7.1244	6.8691	7.0455	7.0055	8.7363	8.7626	7.1627	9.7667	8.6521	**6.2329**	6.2407	6.2363	6.2516	6.2372
		ylag = 2	11.0439	10.7561	12.2438	10.6429	10.6528	10.0306	9.8203	10.6094	10.4840	6.5497	6.4376	6.4553	**6.4374**	6.4481	6.4449
		ylag = 3	17.4139	17.5350	17.2392	17.3042	17.5022	8.3359	8.3815	8.4707	9.9887	10.1785	**6.2347**	6.2652	6.2831	6.2752	6.2680
	MAE	ylag = 0	1.0612	1.0519	**1.0261**	1.0630	1.0566	5.9036	5.3638	4.7569	6.4520	7.7889	1.2630	1.2669	1.2704	1.2639	1.2681
		ylag = 1	0.8717	0.8712	0.8882	0.8768	**0.8666**	5.1363	9.3408	13.8799	5.0138	10.1923	0.8999	0.8995	0.9049	0.9064	0.8962
		ylag = 2	1.0997	1.1022	1.1035	1.1052	1.0997	4.6915	5.1086	5.6793	12.5968	4.0567	0.8930	0.8931	0.8970	0.8979	**0.8913**
		ylag = 3	1.2696	1.2805	1.2701	1.2853	1.2791	2.8735	8.1607	4.4920	4.2530	3.5002	0.9083	0.9083	0.9180	0.9118	**0.9067**
	MAPE	ylag = 0	0.7629	0.7456	**0.7438**	0.7513	0.7508	5.0463	6.4018	5.9794	10.0674	6.3976	0.8460	0.8459	0.8459	0.8478	0.8694
		ylag = 1	0.6344	**0.6230**	0.6278	0.6273	0.6233	3.3919	3.6009	5.8423	19.4989	5.7179	0.6640	0.6515	0.6568	0.6712	0.6793
		ylag = 2	0.7168	0.7218	0.7029	0.7286	0.7223	3.7244	3.3966	3.8396	5.4955	3.6486	0.6939	**0.6699**	0.6896	0.6890	0.7071
		ylag = 3	0.8412	0.8475	0.8158	0.8522	0.8493	3.5869	5.4226	2.2529	5.6902	5.3386	0.7224	**0.6985**	0.7231	0.7471	0.7355

Note: the grey shadowed result means the model outperforms the benchmark, the bold result represents the best performance under the empirical setting.

Appendix

Table A Robustness test results (initial window size is 20 quarters)

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=1/3	MSE	ylag = 0	1.5976	1.6148	**1.2742**	1.6168	1.5782	3.5064	5.8964	3.6110	7.1562	2.7219	1.7387	1.7426	1.7415	1.7421	1.7438
		ylag = 1	2.6381	2.7331	1.9677	2.6865	2.6400	5.1092	4.7888	3.3558	19.1769	2.9179	1.7842	**1.7818**	1.7925	1.7979	1.8026
		ylag = 2	2.7983	2.8991	2.2218	2.8526	2.8025	1.9277	4.7633	3.0478	18.4798	4.7796	1.7969	**1.7947**	1.7985	1.7959	1.7981
		ylag = 3	3.0518	3.1928	2.4419	3.1196	3.0514	2.4194	3.2026	1.9208	13.6115	3.0140	1.7978	1.7954	**1.7948**	1.7990	1.8044
	MAE	ylag = 0	0.5279	0.5261	**0.4930**	0.5318	0.5237	0.9950	1.2732	1.1756	1.5737	1.0265	0.5723	0.5785	0.5778	0.5715	0.5737
		ylag = 1	0.5941	0.5951	**0.5457**	0.5989	0.5913	0.9572	1.0549	0.8902	1.8285	0.8600	0.5612	0.5583	0.5684	0.5733	0.5713
		ylag = 2	0.6184	0.6205	0.5762	0.6225	0.6161	0.6861	0.9289	0.7660	1.8163	0.9644	**0.5601**	0.5696	0.5681	0.5621	0.5614
		ylag = 3	0.6524	0.6556	0.6141	0.6592	0.6506	0.8059	0.9291	0.7355	1.7871	0.8295	0.5661	0.5771	**0.5639**	0.5707	0.5736
	MAPE	ylag = 0	2.1828	2.8078	1.2408	2.7151	61.3284	4.7124	11.2789	5.5340	4.5501	4.2776	0.8319	0.8590	0.8410	0.8329	**0.8242**
		ylag = 1	1.1086	1.1420	1.6037	1.1074	1.1166	3.8039	4.6960	4.0382	2.9307	2.5793	**0.8480**	0.8484	0.8521	0.8576	0.8690
		ylag = 2	1.2115	1.8159	1.5499	1.1122	1.1845	3.5189	1.5357	5.7516	1.4309	2.6192	0.8269	0.8763	**0.8234**	0.8389	0.8263
		ylag = 3	1.3461	2.4221	2.3720	1.2736	4.0600	2.4102	33.7072	3.2227	2.8622	2.1986	**0.8336**	0.8549	0.8378	0.8549	0.8626
h=2/3	MSE	ylag = 0	1.7037	1.6478	2.6956	**1.6281**	1.7154	2.6293	11.0425	3.4651	70.6680	3.4563	1.7483	1.7498	1.7505	1.7576	1.7502
		ylag = 1	3.3010	3.1785	4.4850	3.0045	3.3157	4.1745	2.8927	2.3526	9.9685	5.8679	1.8272	1.8298	1.8316	1.8360	**1.7755**
		ylag = 2	3.5058	**0.5665**	4.7951	3.1853	3.5223	4.1072	4.6641	4.4364	6.1896	2.5023	1.8113	1.8169	1.7886	1.7718	1.8263
		ylag = 3	3.7906	3.6522	5.1877	3.4346	3.8075	6.5022	5.9777	2.3346	7.6641	2.9476	1.8148	1.8197	1.8192	**1.7941**	1.8223
	MAE	ylag = 0	0.5353	0.5420	0.5880	**0.5306**	0.5417	0.9005	1.3310	1.0382	2.8239	1.0811	0.5854	0.5837	0.5893	0.5956	0.5880
		ylag = 1	0.6235	0.6217	0.6608	0.6102	0.6292	0.8637	0.7984	0.7098	1.6360	1.1112	0.5649	0.5669	0.5721	0.5760	**0.5634**
		ylag = 2	0.6526	1.1269	0.6955	0.6368	0.6581	0.8065	0.9866	0.7793	2.5905	0.8284	**0.5630**	0.5669	0.5698	0.5714	0.5707
		ylag = 3	0.6873	0.6868	0.7353	0.6718	0.6921	0.8120	1.0979	0.7516	1.4728	0.8700	**0.5677**	0.5688	0.5785	0.5764	0.5694
	MAPE	ylag = 0	1.2761	4.3783	2.2891	1.3198	1.3018	16.7407	9.1096	5.2024	7.0417	6.1800	0.8264	**0.8262**	0.8351	0.8618	0.8371
		ylag = 1	1.9805	2.6730	3.5594	2.4835	3.2188	2.5530	7.9899	2.4000	2.4755	6.2047	**0.8393**	0.8544	0.8537	0.8849	0.8612
		ylag = 2	1.4129	1.9217	2.7847	2.4626	1.5209	2.6897	2.1782	1.7794	6.7695	2.2319	**0.8192**	0.8491	0.8429	0.8640	0.8376
		ylag = 3	1.7093	1.8579	1.9421	1.7813	2.6025	3.9086	2.6469	2.2062	1.5641	3.8972	0.8378	0.8510	0.8986	0.8755	**0.8311**

Table A Robustness test results (initial window size is 20 quarters) (continued)

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=1	MSE	ylag = 0	1.7634	**1.6936**	1.8011	1.6965	1.7688	3.5113	3.3619	5.1367	7.9653	5.0521	1.7374	1.7406	1.7375	1.7471	1.7365
		ylag = 1	3.4913	3.3190	3.4928	3.3398	3.5048	2.9775	3.6869	2.1776	6.8145	3.7835	**1.7840**	1.7923	1.7853	1.8018	1.7872
		ylag = 2	3.7599	3.5207	3.7630	3.6339	3.7790	2.0692	3.0395	2.3653	4.4994	3.0088	**1.7925**	1.7958	1.7952	1.8081	1.8001
		ylag = 3	4.1495	3.8763	4.1494	3.9906	4.1654	8.5547	3.3493	6.4882	7.3651	3.7305	**1.7982**	1.7983	1.7998	1.8179	1.8022
	MAE	ylag = 0	0.5556	**0.5508**	0.5629	0.5522	0.5542	1.3472	1.2662	1.4870	1.8395	1.4571	0.5710	0.5731	0.5710	0.5801	0.5711
		ylag = 1	0.6368	0.6210	0.6377	0.6295	0.6388	0.8386	0.8284	0.7617	1.2706	0.9075	**0.5612**	0.5685	0.5629	0.5725	0.5670
		ylag = 2	0.6621	0.6429	0.6632	0.6571	0.6634	0.7530	0.8661	0.7566	1.2061	0.9004	**0.5590**	0.5634	0.5607	0.5599	0.5693
		ylag = 3	0.6948	0.6713	0.6962	0.6860	0.6969	1.2455	0.9948	1.1823	1.2922	0.9819	0.5684	**0.5670**	0.5693	0.5784	0.5738
	MAPE	ylag = 0	1.5365	1.1842	2.1055	1.4407	1.7158	8.8234	48.5065	5.9791	2.5277	10.1402	0.8295	0.8550	0.8294	0.8461	**0.8198**
		ylag = 1	1.9727	1.9876	3.1748	2.1654	2.1223	2.8207	2.8507	2.6426	4.8234	4.1664	**0.8467**	0.8629	0.8499	0.8809	0.8734
		ylag = 2	1.9675	2.9755	3.0618	3.3618	2.4194	2.5555	3.9430	5.1348	1.7630	3.6361	0.8347	0.8491	0.8383	**0.8301**	0.8654
		ylag = 3	8.5710	1.9178	1.9537	2.1436	7.8773	2.9403	3.8981	6.8627	2.0580	6.7820	**0.8568**	0.8642	0.8592	0.8852	0.8958
h=2	MSE	ylag = 0	**1.7447**	1.7658	1.7560	1.7547	1.7461	5.1382	3.6218	3.5609	5.2307	4.9101	1.7469	1.7464	1.7484	1.7553	1.7465
		ylag = 1	1.8358	1.8649	1.8482	1.8439	1.8419	8.7517	3.8703	2.8532	4.0550	1.9745	**1.7881**	1.7883	1.7887	1.7975	1.8232
		ylag = 2	1.9258	1.9746	1.9377	1.9389	1.9407	2.8470	2.9180	2.2874	6.4499	3.7648	**1.7930**	1.7964	1.7967	1.8116	1.8079
		ylag = 3	2.0704	2.1358	2.0788	2.0834	2.0828	4.6158	5.2208	5.4454	4.6650	4.2363	**1.7941**	1.8257	1.7993	1.8120	1.8094
	MAE	ylag = 0	**0.5586**	0.5660	0.5641	0.5645	0.5646	1.5602	1.3489	1.3599	1.7547	1.4107	0.5796	0.5789	0.5814	0.5856	0.5744
		ylag = 1	**0.5555**	0.5624	0.5583	0.5599	0.5618	0.9982	0.9897	0.8965	1.1710	0.6520	0.5617	0.5629	0.5622	0.5665	0.5561
		ylag = 2	0.5717	0.5797	0.5758	0.5784	0.5783	0.8579	0.8793	0.7164	1.3403	1.0307	0.5607	0.5645	0.5638	0.5732	**0.5512**
		ylag = 3	0.6005	0.6123	0.6045	0.6020	0.6083	1.0783	1.1337	1.0417	1.2228	1.0789	0.5623	0.5685	0.5653	0.5715	**0.5535**
	MAPE	ylag = 0	1.1791	1.1842	1.2193	1.2080	1.2619	4.8664	33.5959	3.3862	2.7644	15.0172	0.8436	0.8478	0.8526	0.8627	**0.8134**
		ylag = 1	1.9762	1.9260	1.8733	1.7120	2.0667	5.1849	4.3102	4.9613	5.1654	5.3946	0.8587	0.8618	0.8595	0.8753	**0.8320**
		ylag = 2	1.6874	1.7303	5.9149	5.3876	2.1839	7.9920	3.5817	1.0014	3.1730	3.2203	0.8529	0.8599	0.8577	0.8772	**0.8431**
		ylag = 3	1.3208	1.3848	1.4992	1.3504	1.7172	12.2058	3.0317	2.4159	7.4286	2.6644	0.8593	0.8681	0.8646	0.8765	**0.8507**

Table A Robustness test results (initial window size is 20 quarters) (continued)

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=3	MSE	ylag = 0	1.7465	1.7518	1.7650	1.7551	1.7491	3.6627	7.4636	3.5330	12.0800	3.3307	1.7424	1.7423	1.7424	1.7663	**1.7352**
		ylag = 1	1.7891	1.7960	1.8074	1.7999	1.7938	19.3677	10.9300	22.9084	17.9736	15.0518	1.7898	1.7899	1.7896	1.8020	**1.7878**
		ylag = 2	1.9262	1.9335	1.9336	1.9380	1.9429	8.0169	3.9765	2.6503	26.5919	14.8594	1.7957	**1.7930**	1.7951	1.8304	1.7935
		ylag = 3	1.9662	1.9748	1.9674	1.9803	1.9806	3.9402	3.9853	12.6280	5.7100	9.7226	1.7990	**1.7965**	1.7968	1.8320	1.7988
	MAE	ylag = 0	**0.5561**	0.5605	0.5626	0.5593	0.5569	1.3134	1.6230	1.2793	1.8419	1.2042	0.5752	0.5745	0.5753	0.6000	0.5741
		ylag = 1	**0.5604**	0.5656	0.5664	0.5642	0.5646	3.0396	1.5951	2.9485	2.0817	2.0057	0.5645	0.5645	0.5644	0.5804	0.5631
		ylag = 2	0.5825	0.5861	0.5886	0.5860	0.5878	1.3333	1.1825	0.9162	2.0374	1.2070	0.5617	0.5604	0.5612	0.5714	**0.5585**
		ylag = 3	0.5926	0.5963	0.6002	0.5960	0.5981	1.1179	1.0788	3.8725	1.1901	1.3559	0.5670	**0.5655**	0.5662	0.5765	0.5695
	MAPE	ylag = 0	1.1552	1.2665	17.1287	1.1554	1.1213	3.9669	4.2177	22.5421	4.2258	4.0044	0.8316	**0.8292**	0.8319	0.8795	0.8455
		ylag = 1	1.1854	1.3590	1.9024	1.2423	1.1747	5.8245	5.2726	3.4712	2.0840	2.3707	0.8374	0.8385	**0.8373**	0.8601	0.8457
		ylag = 2	1.1015	1.1604	1.3451	1.0919	1.1316	3.4291	3.8867	5.2627	2.1423	3.5616	0.8261	**0.8238**	0.8255	0.8529	0.8311
		ylag = 3	1.1328	1.2261	1.1261	1.1223	1.2888	4.6066	4.5704	5.7532	1.9585	2.8959	**0.8319**	0.8334	0.8375	0.8536	0.8504

Note: the grey shadowed result means the model outperforms the benchmark, the bold result represents the best performance under the empirical setting.

Table B Robustness test results (initial window size is 30 quarters)

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=1/3	MSE	ylag = 0	1.7097	1.7281	**1.3623**	1.7299	1.6887	3.5575	9.8573	4.7380	10.7142	4.6589	1.8593	1.8647	1.8594	1.8653	1.8655
		ylag = 1	2.8247	2.9265	2.1046	2.8760	2.8268	2.0013	4.7366	3.6530	37.2514	2.8184	1.9106	**1.9046**	1.9156	1.9173	1.9242
		ylag = 2	2.9972	3.1052	2.3786	3.0548	3.0019	6.9288	4.7787	6.9142	21.6949	3.8611	1.9256	1.9225	1.9251	**1.9223**	1.9252
		ylag = 3	3.2696	3.4209	2.6150	3.3407	3.2693	4.0865	3.3401	2.4684	12.7087	4.4478	1.9250	**1.9180**	1.9226	1.9249	1.9282
	MAE	ylag = 0	0.5535	0.5518	**0.5157**	0.5580	0.5488	1.1184	1.5330	1.0807	1.9919	1.2172	0.5971	0.6045	0.5983	0.5989	0.5980
		ylag = 1	0.6219	0.6227	**0.5684**	0.6270	0.6188	0.7458	0.8944	0.9551	1.8633	0.9713	0.5879	0.5812	0.5915	0.5904	0.5905
		ylag = 2	0.6464	0.6486	0.6019	0.6508	0.6440	0.8813	1.0015	0.9794	1.8794	0.8853	0.5902	0.5982	0.5886	**0.5885**	0.5937
		ylag = 3	0.6821	0.6853	0.6413	0.6869	0.6800	0.8550	0.9472	0.8127	1.6943	1.0065	0.5924	0.6003	**0.5912**	0.5989	0.5961
	MAPE	ylag = 0	2.3138	2.9840	1.3062	2.8865	65.7143	13.7938	26.2592	3.9558	5.1461	3.7423	0.8656	0.8924	0.8670	0.8686	**0.8534**
		ylag = 1	1.1603	1.1960	1.6921	1.1623	1.1685	6.0245	1.9498	6.1847	2.4769	4.9153	0.8809	0.8764	0.8767	**0.8740**	0.8909
		ylag = 2	1.2700	1.3962	1.6354	1.1670	1.2416	3.9934	7.3459	10.4545	5.3955	3.2109	0.8670	0.9130	**0.8516**	0.8714	0.8595
		ylag = 3	1.4148	2.5700	2.5164	1.3345	4.3285	2.2538	3.4492	6.0049	5.8665	4.9283	**0.8656**	0.8793	0.8706	0.8858	0.8834
h=2/3	MSE	ylag = 0	1.8196	1.7594	2.8829	**1.7394**	1.8312	3.4217	4.8499	4.1351	13.5320	4.2198	1.8676	1.8706	1.8675	1.8730	1.8689
		ylag = 1	3.5310	3.3987	4.8013	3.2127	3.5459	9.5012	5.2155	1.9005	23.9533	4.6851	1.9530	1.9549	1.9521	1.9562	**1.8990**
		ylag = 2	3.7567	3.6072	5.1409	3.4126	3.7730	5.6544	6.5218	3.7476	18.9563	3.0808	1.9395	1.9423	**1.8923**	1.9116	1.9539
		ylag = 3	4.0654	3.9134	5.5660	3.6829	4.0822	4.9234	5.7263	2.5875	3.6241	4.8226	1.9421	1.9458	**1.9162**	1.9424	1.9496
	MAE	ylag = 0	0.5579	0.5637	0.6147	**0.5557**	0.5663	1.0161	1.1498	1.1206	2.1072	1.1937	0.6086	0.6094	0.6084	0.6134	0.6094
		ylag = 1	0.6480	0.6436	0.6884	0.6338	0.6527	1.0240	1.1169	0.7558	2.0470	1.1290	0.5873	0.5874	**0.5859**	0.5919	0.5871
		ylag = 2	0.6835	0.6811	0.7306	0.6667	0.6875	0.9196	1.1492	0.8666	1.8157	0.8780	0.5900	0.5925	**0.5877**	0.5929	0.5955
		ylag = 3	0.7226	0.7176	0.7756	0.7060	0.7261	0.8881	1.1775	0.8661	2.2196	1.0753	0.5934	0.5988	**0.5904**	0.5980	0.5940
	MAPE	ylag = 0	1.3389	4.6634	2.4254	1.3948	1.3717	6.7692	6.9079	7.1153	2.8389	3.9769	**0.8546**	0.8616	0.8554	0.8760	0.8625
		ylag = 1	2.0929	2.8307	3.7846	2.6334	3.4187	3.0258	5.7307	10.4701	4.7536	2.6486	0.8673	0.8786	**0.8660**	0.8904	0.8871
		ylag = 2	1.4869	2.0268	2.9596	2.6139	1.6001	2.9955	2.0133	2.0520	1.8749	2.0890	0.8689	0.8687	0.8681	0.8814	**0.8656**
		ylag = 3	1.8093	1.9653	2.0621	1.8873	2.7675	6.6668	3.1901	5.4643	2.1233	2.8645	0.8691	0.8719	0.9225	0.8928	**0.8592**

Table B Robustness test results (initial window size is 30 quarters) (continued)

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=1	MSE	ylag = 0	1.8839	**1.8084**	1.9241	1.8117	1.8911	2.9067	3.6243	3.2352	24.8661	3.6761	1.8604	1.8632	1.8604	1.8655	1.8590
		ylag = 1	3.7340	3.5491	3.7362	3.5705	3.7494	2.9718	1.9134	3.4870	9.8811	3.0228	1.9110	1.9167	**1.9102**	1.9210	1.9114
		ylag = 2	4.0281	3.7710	4.0319	3.8922	4.0492	5.0154	2.3051	2.3031	17.8920	3.3479	1.9230	1.9234	**1.9226**	1.9373	1.9274
		ylag = 3	4.4489	4.1550	4.4492	4.2786	4.4663	3.4922	4.9481	2.1648	10.5136	4.1731	1.9258	1.9256	1.9272	1.9310	**1.9255**
	MAE	ylag = 0	0.5777	**0.5717**	0.5859	0.5734	0.5787	1.2995	1.2588	1.3513	2.2437	1.3230	0.5989	0.5992	0.5986	0.6011	0.5976
		ylag = 1	0.6584	0.6426	0.6608	0.6497	0.6622	0.8331	0.7440	0.8313	1.3667	0.9715	0.5862	0.5908	**0.5862**	0.5918	0.5886
		ylag = 2	0.6907	0.6707	0.6931	0.6850	0.6946	0.8794	0.7429	0.7448	1.3593	0.9335	0.5883	0.5922	**0.5882**	0.5886	0.5949
		ylag = 3	0.7276	0.7023	0.7306	0.7190	0.7303	0.8687	1.1314	0.8103	1.5113	1.1362	0.5951	**0.5933**	0.5951	0.5979	0.5958
	MAPE	ylag = 0	1.6120	1.2331	2.2232	1.5100	1.8089	2.9880	4.3181	8.4598	3.8382	6.1871	0.8668	0.8869	0.8668	0.8643	**0.8537**
		ylag = 1	2.0723	2.0903	3.3647	2.2806	2.2382	3.9917	2.5618	2.4478	5.3030	1.7520	0.8765	0.8858	**0.8765**	0.8916	0.8980
		ylag = 2	2.0739	3.1562	3.2506	3.5710	2.5626	3.7593	7.1889	1.8393	2.6567	4.6646	0.8716	0.8843	0.8716	**0.8643**	0.8962
		ylag = 3	9.1657	2.0236	2.0653	2.2688	8.4232	2.3436	2.4075	1.7527	1.9582	28.4832	0.8888	0.8934	0.8882	**0.8842**	0.9161
h=2	MSE	ylag = 0	1.8647	1.8853	1.8750	1.8736	1.8672	4.3992	3.4295	4.2344	8.2361	22.8155	1.8659	1.8663	1.8660	1.8718	**1.8637**
		ylag = 1	1.9677	1.9987	1.9804	1.9755	1.9743	4.8766	4.2785	5.5204	5.3938	2.3737	1.9115	**1.9114**	1.9119	1.9175	1.9460
		ylag = 2	2.0634	2.1157	2.0742	2.0749	2.0801	3.4703	7.2372	11.7015	7.1462	6.7298	**1.9197**	1.9198	1.9198	1.9346	1.9323
		ylag = 3	2.2212	2.2912	2.2302	2.2350	2.2347	7.0970	6.3771	2.9058	5.8292	2.5958	1.9292	1.9510	**1.9219**	1.9347	1.9335
	MAE	ylag = 0	**0.5822**	0.5869	0.5858	0.5859	0.5898	1.4441	1.3198	1.3967	1.9584	1.7525	0.6035	0.6038	0.5962	0.6056	0.6037
		ylag = 1	0.5871	0.5940	0.5888	0.5909	0.5942	1.0390	1.0117	0.9902	1.3379	0.7860	0.5840	0.5847	**0.5739**	0.5832	0.5840
		ylag = 2	0.6021	0.6105	0.6038	0.6073	0.6101	0.9563	1.2425	1.2364	1.4985	1.2422	0.5844	0.5854	**0.5718**	0.5925	0.5851
		ylag = 3	0.6340	0.6466	0.6376	0.6350	0.6426	1.1419	1.2223	0.9129	1.3979	0.8983	0.5857	0.5893	**0.5733**	0.5910	0.5861
	MAPE	ylag = 0	1.2267	1.2278	1.2660	1.2530	1.3173	13.5427	5.0557	3.3454	5.1075	4.0076	0.8776	0.8831	**0.8423**	0.8902	0.8844
		ylag = 1	2.1027	2.0479	1.9904	1.8177	2.1978	9.7800	6.8531	3.4215	2.8250	5.9000	0.8862	0.8875	**0.8500**	0.8923	0.8860
		ylag = 2	1.7809	1.8274	6.3165	5.7509	2.3183	2.9625	3.2783	4.2072	4.4522	2.6564	0.8836	0.8850	**0.8674**	0.8965	0.8845
		ylag = 3	1.3958	1.4611	1.5820	1.4252	1.8224	4.3630	3.3638	3.5100	3.5574	2.3435	0.8894	0.8931	**0.8735**	0.8977	0.8900

Table B Robustness test results (initial window size is 30 quarters) (continued)

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=3	MSE	ylag = 0	1.8675	1.8729	1.8870	1.8750	1.8702	3.7666	4.4850	4.2309	6.3761	3.2394	1.8620	1.8622	1.8620	1.8733	**1.8524**
		ylag = 1	1.9136	1.9198	1.9326	1.9223	1.9187	7.3458	14.0424	38.9836	19.1309	25.6358	1.9139	1.9137	1.9137	1.9200	**1.9118**
		ylag = 2	2.0625	2.0709	2.0707	2.0738	2.0809	23.7128	4.1338	8.0502	9.9207	3.8777	1.9224	**1.9196**	1.9218	1.9579	1.9216
		ylag = 3	2.1081	2.1172	2.1095	2.1226	2.1240	5.8570	7.8909	3.9001	7.6056	5.3430	1.9245	1.9223	**1.9222**	1.9585	1.9243
	MAE	ylag = 0	**0.5777**	0.5821	0.5842	0.5802	0.5784	1.3303	1.4750	1.3141	1.7827	1.1224	0.5989	0.5986	0.5990	0.6097	0.5957
		ylag = 1	**0.5827**	0.5868	0.5880	0.5850	0.5871	1.4107	1.8829	1.7752	2.3547	1.9621	0.5878	0.5873	0.5878	0.5967	0.5849
		ylag = 2	0.6074	0.6125	0.6134	0.6101	0.6134	1.8427	1.1000	1.2714	1.5989	1.1187	0.5888	0.5872	0.5884	0.5965	**0.5870**
		ylag = 3	0.6198	0.6240	0.6281	0.6227	0.6267	1.2193	1.2983	1.0195	1.4643	1.1323	0.5909	0.5900	**0.5900**	0.5999	0.5934
	MAPE	ylag = 0	1.2051	1.3235	18.3448	1.2056	1.1689	4.3821	14.8540	3.5147	3.7138	3.8976	0.8648	**0.8629**	0.8651	0.8816	0.8762
		ylag = 1	1.2381	1.4223	2.0075	1.2990	1.2266	2.4573	3.5021	24.8355	2.2848	23.9937	0.8686	0.8687	**0.8686**	0.8754	0.8721
		ylag = 2	1.1510	1.2121	1.4119	1.1411	1.1837	10.4790	5.0620	3.5208	1.9808	5.6130	0.8643	**0.8612**	0.8639	0.8833	0.8703
		ylag = 3	1.1873	1.2875	1.1786	1.1746	1.3565	4.9313	7.7204	5.5814	4.3317	8.9883	**0.8629**	0.8652	0.8689	0.8803	0.8811

Note: the grey shadowed result means the model outperforms the benchmark, the bold result represents the best performance under the empirical setting.

Table C Robustness test results (initial window size is 50 quarters)

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=1/3	MSE	ylag = 0	1.9775	1.9978	**1.5712**	2.0002	1.9524	3.3854	5.0868	3.3649	35.2790	20.9419	2.1531	2.1550	2.1520	2.1616	2.1580
		ylag = 1	3.2851	3.4034	2.4428	3.3440	3.2866	4.9716	7.2677	2.2578	13.0946	5.5329	2.2129	2.2139	**2.2115**	2.2180	2.2267
		ylag = 2	3.4892	3.6153	2.7652	3.5557	3.4938	**2.0283**	4.2335	5.1856	16.9725	9.6399	2.2296	2.2188	2.2282	2.2250	2.2292
		ylag = 3	3.8132	3.9903	3.0457	3.8953	3.8117	5.7466	4.8077	3.3967	14.9968	8.8700	2.2282	**2.2194**	2.2277	2.2250	2.2306
	MAE	ylag = 0	0.5992	0.5960	**0.5554**	0.6030	0.5928	1.0496	1.2728	1.1496	2.9485	1.3923	0.6489	0.6528	0.6487	0.6546	0.6506
		ylag = 1	0.6806	0.6807	**0.6178**	0.6851	0.6760	0.9937	1.1892	0.8388	1.8361	1.0415	0.6369	0.6371	0.6321	0.6411	0.6399
		ylag = 2	0.7082	0.7092	0.6572	0.7126	0.7043	0.6983	0.9902	0.8715	3.2557	1.2715	0.6389	0.6395	0.6412	**0.6349**	0.6400
		ylag = 3	0.7513	0.7540	0.7033	0.7562	0.7480	1.0873	1.1791	0.8998	1.9894	1.1461	0.6407	0.6430	**0.6407**	0.6447	0.6450
	MAPE	ylag = 0	2.5626	3.3437	1.3885	3.2261	76.6114	5.4610	82.3446	5.3826	9.3112	6.6565	0.8255	0.8349	**0.8255**	0.8396	0.8309
		ylag = 1	1.1924	1.2327	1.7615	1.1795	1.1851	4.4404	4.6628	3.4480	2.3870	2.3251	0.8395	**0.8386**	0.8440	0.8533	0.8514
		ylag = 2	1.2365	1.1173	0.9508	1.1674	1.1942	3.6926	3.5654	8.4444	4.0906	4.7371	0.7952	0.8084	**0.7925**	0.8022	0.8188
		ylag = 3	1.3488	1.3455	1.0483	1.3498	4.7596	1.7359	10.4239	4.1689	2.6296	2.2930	0.8212	0.8222	**0.8209**	0.8369	0.8453
h=2/3	MSE	ylag = 0	2.1067	2.0372	3.3477	**2.0107**	2.1176	4.8815	6.1643	3.5667	28.6422	6.9953	2.1648	2.1634	2.1634	2.1711	2.1666
		ylag = 1	4.1120	3.9577	5.5957	3.7391	4.1285	6.3276	3.4866	2.9102	22.0727	3.8128	2.2662	2.2645	2.2647	2.2688	**2.1972**
		ylag = 2	4.3800	4.2056	5.9980	3.9765	4.3984	8.1799	7.3744	6.5315	18.2302	2.6833	2.2498	2.2532	**2.1926**	2.2613	2.2160
		ylag = 3	4.7460	4.5687	6.5021	4.2966	4.7650	6.0345	5.7057	3.3369	31.1664	4.0592	2.2523	2.2555	**2.2205**	2.2572	2.2493
	MAE	ylag = 0	0.6064	0.6152	0.6715	**0.5996**	0.6103	1.1302	1.4524	1.0811	2.5734	1.3798	0.6639	0.6637	0.6633	0.6705	0.6652
		ylag = 1	0.7141	0.7105	0.7583	0.6963	0.7178	1.1107	0.9735	0.9320	3.8951	0.9888	0.6396	0.6396	0.6388	0.6458	**0.6369**
		ylag = 2	0.7555	0.7545	0.8067	0.7345	0.7582	1.0422	1.1618	1.0038	3.3257	0.8927	0.6449	**0.6427**	0.6446	0.6446	0.6504
		ylag = 3	0.7993	0.7956	0.8580	0.7774	0.8021	1.0325	1.2457	0.9387	2.4619	0.9892	0.6462	**0.6450**	0.6477	0.6506	0.6482
	MAPE	ylag = 0	1.4138	5.2886	2.6827	1.4749	1.3796	14.5483	11.7899	11.2353	4.8726	6.2789	0.8338	0.8422	**0.8335**	0.8629	0.8414
		ylag = 1	2.1460	2.7542	3.5967	2.6982	3.6049	2.6666	6.8150	2.3275	4.1663	6.1973	0.8530	0.8679	**0.8527**	0.8831	0.8698
		ylag = 2	1.3642	1.6348	2.2550	1.5086	1.3993	4.3596	2.0350	12.2430	10.6467	8.5804	0.8363	0.8509	**0.8271**	0.8475	0.8562
		ylag = 3	1.5708	1.5436	1.6375	1.7425	1.4430	4.5965	3.2983	6.1570	5.8556	3.0034	0.8383	0.8530	**0.8364**	0.8609	0.8458

Table C Robustness test results (initial window size is 50 quarters) (continued)

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=1	MSE	ylag = 0	2.1831	**2.0958**	2.2295	2.0986	2.1900	3.8747	4.3381	4.6734	10.3953	4.3562	2.1543	2.1570	2.1543	2.1591	2.1521
		ylag = 1	4.3506	4.1340	4.3519	4.1596	4.3674	4.8329	8.9683	4.7907	6.5774	13.2058	**2.2128**	2.2187	2.2133	2.2226	2.2135
		ylag = 2	4.6986	4.3976	4.7021	4.5401	4.7221	2.8900	4.4126	**1.8293**	12.7092	3.6054	2.2250	2.2284	2.2270	2.2458	2.2321
		ylag = 3	5.1956	4.8509	5.1945	4.9964	5.2156	8.3082	4.6834	2.2285	6.4636	5.5638	2.2286	**2.2265**	2.2298	2.2349	2.2282
	MAE	ylag = 0	0.6312	**0.6242**	0.6405	0.6263	0.6312	1.4015	1.4037	1.4291	2.1444	1.4269	0.6508	0.6510	0.6508	0.6533	0.6491
		ylag = 1	0.7281	0.7093	0.7298	0.7170	0.7310	0.9293	1.1225	1.0074	1.2908	1.1150	**0.6374**	0.6405	0.6374	0.6395	0.6376
		ylag = 2	0.7673	0.7430	0.7694	0.7600	0.7692	0.8805	0.9775	0.7512	1.3586	0.8938	0.6391	0.6412	**0.6390**	0.6425	0.6446
		ylag = 3	0.8061	0.7763	0.8091	0.7954	0.8083	1.1269	1.1435	0.8330	1.3749	1.3653	0.6435	**0.6385**	0.6425	0.6448	0.6434
	MAPE	ylag = 0	1.7520	1.2949	2.4585	1.6320	1.9836	4.1236	5.1097	5.9467	6.9186	4.5902	0.8281	0.8432	0.8281	0.8285	**0.8205**
		ylag = 1	2.1250	2.1146	2.1303	2.4455	2.2285	2.3239	3.0706	3.6773	1.6040	4.8000	0.8403	0.8459	0.8403	0.8396	**0.8358**
		ylag = 2	2.1493	3.1572	3.5186	3.8097	2.8263	3.4087	7.6506	2.5678	1.7761	6.0529	**0.8052**	0.8056	0.8053	0.8087	0.8230
		ylag = 3	10.2366	1.8473	1.9925	2.4668	9.6830	2.3203	6.4836	5.6761	5.0076	2.5670	0.8270	**0.8185**	0.8256	0.8303	0.8415
h=2	MSE	ylag = 0	**2.1593**	2.1838	2.1707	2.1694	2.1636	3.9673	4.4282	3.4572	7.2868	3.8276	2.1624	2.1617	2.1623	2.1677	2.1654
		ylag = 1	2.2753	2.3140	2.2904	2.2846	2.2836	3.7134	27.8179	3.8157	5.9366	8.0860	2.2185	**2.2181**	2.2190	2.2264	2.2654
		ylag = 2	2.3894	2.4530	2.4018	2.4029	2.4089	2.9166	3.3948	4.5362	6.0442	4.4432	2.2255	2.2267	**2.2250**	2.2410	2.2462
		ylag = 3	2.5727	2.6580	2.5841	2.5885	2.5887	6.1233	3.6442	3.1266	7.9466	4.2569	2.2297	2.2632	**2.2294**	2.2410	2.2475
	MAE	ylag = 0	**0.6326**	0.6389	0.6363	0.6369	0.6409	1.6020	1.3936	1.3240	1.8822	1.3845	0.6571	0.6555	0.6530	0.6596	0.6570
		ylag = 1	**0.6308**	0.6407	0.6329	0.6350	0.6403	1.4273	1.0195	0.9928	1.3741	1.1050	0.6373	0.6375	0.6332	0.6382	0.6373
		ylag = 2	0.6483	0.6595	0.6499	0.6541	0.6576	0.9008	0.9826	0.9590	1.4908	1.1697	0.6362	0.6369	**0.6265**	0.6421	0.6371
		ylag = 3	0.6848	0.6998	0.6883	0.6853	0.6927	1.3436	0.9558	1.0589	1.5070	1.1048	0.6377	0.6413	**0.6281**	0.6403	0.6382
	MAPE	ylag = 0	1.3025	1.3111	1.3449	1.3328	1.3897	3.3664	4.2483	7.4743	5.6843	3.0915	0.8327	0.8328	0.8325	0.8454	**0.8247**
		ylag = 1	2.2345	2.1860	2.0906	1.8817	2.3426	8.2854	6.6796	5.5877	2.2064	3.5164	0.8358	0.8358	**0.8356**	0.8498	0.8430
		ylag = 2	1.8705	1.8531	7.1821	6.4278	2.5045	4.5916	2.3944	3.3402	8.7721	7.8526	0.8092	0.8079	0.8082	0.8205	**0.7974**
		ylag = 3	1.4403	1.4520	1.5831	1.4611	1.9161	6.8055	3.3318	3.6774	5.9337	6.5549	0.8140	0.8173	0.8146	0.8215	**0.8044**

Table C Robustness test results (initial window size is 50 quarters) (continued)

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=3	MSE	ylag = 0	2.1613	2.1679	2.1837	2.1696	2.1638	5.7057	5.4662	4.4879	8.4034	3.9786	2.1584	2.1580	**2.1483**	2.1684	2.1584
		ylag = 1	**2.2170**	2.2245	2.2387	2.2267	2.2221	27.2933	43.3738	26.2873	17.8278	24.1734	2.2198	2.2191	2.2191	2.2280	2.2196
		ylag = 2	2.3904	2.4005	2.4000	2.4028	2.4102	6.8107	4.3173	3.8672	4.1645	7.2529	2.2288	**2.2260**	2.2269	2.2668	2.2282
		ylag = 3	2.4457	2.4567	2.4479	2.4620	2.4611	3.6733	7.9461	16.0023	13.4190	4.8916	2.2303	2.2277	**2.2244**	2.2667	2.2276
	MAE	ylag = 0	**0.6283**	0.6327	0.6350	0.6307	0.6290	1.5691	1.5358	1.3641	1.7829	1.3790	0.6535	0.6533	0.6509	0.6606	0.6535
		ylag = 1	**0.6323**	0.6362	0.6378	0.6344	0.6372	4.7156	2.3975	2.0217	2.1841	2.0033	0.6409	0.6409	0.6394	0.6480	0.6408
		ylag = 2	0.6573	0.6631	0.6646	0.6595	0.6641	2.3929	1.0920	1.1079	2.0793	1.1956	0.6399	0.6388	**0.6371**	0.6443	0.6395
		ylag = 3	0.6719	0.6750	0.6819	0.6744	0.6788	1.1002	1.3498	1.3900	1.7288	1.2330	0.6422	0.6412	**0.6386**	0.6486	0.6411
	MAPE	ylag = 0	1.2382	1.2862	21.2194	1.2432	1.2339	4.4781	5.7910	5.3705	8.3456	5.2182	**0.8307**	0.8313	0.8308	0.8391	0.8487
		ylag = 1	1.2862	1.3729	2.1318	1.3610	1.2957	8.4388	8.4581	26.0079	12.0764	2.7395	0.8328	0.8347	**0.8328**	0.8474	0.8334
		ylag = 2	1.1826	1.1906	1.4044	1.1732	1.1821	3.7137	3.0943	3.1981	3.7192	10.2332	0.8005	0.8015	0.8002	0.8066	**0.7987**
		ylag = 3	1.2647	1.2538	1.2438	1.2497	1.4675	22.1326	3.8818	3.0714	3.6222	3.3742	0.8152	0.8155	0.8224	0.8245	**0.8113**

Note: the grey shadowed result means the model outperforms the benchmark, the bold result represents the best performance under the empirical setting.

Table D Robustness test results (different forecast horizon)

			Std-AR-MIDAS					MS-AR-MIDAS					TVP-AR-MIDAS				
			benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID	benchmark	OS	EA	OCD	OID
h=4	MSE	ylag = 0	2.0580	2.0827	2.0697	2.0937	2.0780	4.1599	4.7066	5.4604	9.4877	4.8796	2.0480	2.0519	**2.0475**	2.0478	2.0535
		ylag = 1	4.2295	4.2361	4.2320	4.2952	4.2372	7.8801	7.8159	7.3294	11.2140	5.3392	2.2678	2.2599	**2.2572**	2.2625	2.2587
		ylag = 2	4.5494	4.5654	4.5536	4.6213	4.5619	3.5663	3.8703	4.9982	3.8950	3.8779	2.1767	2.1772	**2.1741**	2.1787	2.1800
		ylag = 3	4.9196	4.9631	4.9781	5.0316	4.9496	5.5225	6.8030	6.7285	6.1525	4.4192	2.1772	**2.1734**	2.1763	2.1807	2.1798
	MAE	ylag = 0	**0.6181**	0.6227	0.6247	0.6302	0.6206	1.7622	1.4732	1.4726	1.9259	1.3934	0.6195	0.6221	0.6199	0.6207	0.6251
		ylag = 1	0.7051	0.7082	0.7111	0.7115	0.7083	1.8830	1.6534	1.6129	1.9897	1.4258	0.6067	0.6087	**0.6037**	0.6082	0.6058
		ylag = 2	0.7385	0.7437	0.7361	0.7448	0.7371	1.2111	1.1209	1.2299	1.2117	1.0043	0.6002	0.6014	**0.5989**	0.6043	0.6044
		ylag = 3	0.7765	0.7784	0.7765	0.7832	0.7734	1.3346	1.9049	1.3083	1.3543	1.0075	**0.6016**	0.6031	0.6017	0.6062	0.6070
	MAPE	ylag = 0	0.9393	0.9125	0.9354	0.9487	0.9353	4.2444	4.0369	37.5701	3.1510	5.8077	0.8383	0.8395	**0.8380**	0.8434	0.8525
		ylag = 1	1.0489	1.0459	1.0738	1.0558	1.0532	3.3839	2.5035	4.5170	2.3568	5.1978	0.8800	0.8779	**0.8701**	0.8873	0.8829
		ylag = 2	1.0575	1.0531	1.0457	1.0568	1.0340	2.5893	16.2377	2.5427	3.9977	7.9865	0.8418	0.8415	**0.8383**	0.8593	0.8649
		ylag = 3	1.0676	1.0553	1.0592	1.0786	1.0485	4.0936	4.8095	7.1112	49.9072	4.3121	0.8486	0.8496	**0.8484**	0.8681	0.8793
h=8	MSE	ylag = 0	2.0311	2.0474	2.0608	2.0376	**2.0282**	5.6454	5.0866	18.3407	6.0842	5.1901	2.0372	2.0345	2.0337	2.0377	2.0346
		ylag = 1	4.2646	4.3819	4.2919	4.2641	4.2756	4.5226	4.5551	3.2864	3.6443	4.6395	2.0962	2.0930	**2.0921**	2.1059	2.1007
		ylag = 2	4.5650	4.6908	4.5895	4.5643	4.5841	3.7735	3.6081	3.1242	2.6110	3.9326	**2.0718**	2.0886	2.0857	2.0831	2.0835
		ylag = 3	4.8917	4.9453	4.9087	4.8875	4.8975	3.9269	3.7454	2.8624	5.5797	3.7816	2.0859	**2.0760**	2.0841	2.0997	2.0871
	MAE	ylag = 0	0.5918	0.5972	0.6039	0.5944	0.5947	1.4501	1.4499	1.6186	1.4282	1.4328	0.5985	0.5988	0.5960	0.5981	**0.5908**
		ylag = 1	0.6988	0.7065	0.7020	0.6969	0.7009	1.1627	1.2912	1.1143	1.1635	1.3129	0.5920	0.5956	0.5878	0.5918	**0.5865**
		ylag = 2	0.7348	0.7457	0.7381	0.7287	0.7431	1.0310	1.0623	0.9787	1.0588	1.0879	0.5927	0.6030	0.5905	0.5974	**0.5897**
		ylag = 3	0.7643	0.7724	0.7659	0.7548	0.7701	1.5050	1.1236	0.9475	1.2641	1.0602	0.5957	0.5945	0.5944	0.5985	**0.5922**
	MAPE	ylag = 0	0.8886	0.9193	0.9186	0.8940	0.9026	4.8486	8.1003	4.7084	4.0317	4.1077	0.8656	0.8762	0.8658	0.8773	**0.8590**
		ylag = 1	0.9985	1.0286	1.0183	1.0076	1.0145	4.2132	3.6629	4.7383	6.7599	2.7321	0.8693	0.8804	0.8713	0.8824	**0.8639**
		ylag = 2	1.0072	1.0542	1.0370	0.9964	1.0454	6.8847	9.1932	4.4693	4.9121	6.3474	0.8356	0.8577	**0.8225**	0.8470	0.8266
		ylag = 3	1.0410	1.0597	1.0471	1.0015	1.0545	5.2129	2.4237	3.0747	5.8337	4.5833	0.8387	0.8427	**0.8249**	0.8552	0.8367

Note: the grey shadowed result means the model outperforms the benchmark, the bold result represents the best performance under the empirical setting.