Towards Macroeconomic Portfolio Forecasting Model With Multi-source Mixing Data

Xiaoxuan Su*

Tianjin NO.1 High School , Tianjin, China

*Corresponding author: piaolingjiu9@163.com

Abstract. Using China's daily financial data and monthly/quarterly macroeconomic data, this paper constructs a mixed frequency data sampling model (MIDAS) from the perspective of pseudo-out-of-sample forecasting, and adds financial and economic leading factors to compare the macroeconomic prediction accuracy of the four types of combined forecasting models. The results show that the combined forecasting model can reduce the systematic error of macroeconomic forecasting and improve the prediction accuracy. Among them, daily financial data can improve the prediction accuracy of univariate; Whether in MIDAS or traditional forecasting models, monthly/quarterly macroeconomic data can improve the accuracy of macroeconomic forecasting; The macroeconomic forecasting effect of monthly/quarterly macroeconomic data on the macroeconomy is comparable to that of daily financial data on the macroeconomy, or even better than the macroeconomic forecasting effect of daily financial data; The leading items of monthly/quarterly macroeconomic data have a good effect on China's macro forecast.

Keywords: Mixing data; MIDAS model; Macroeconomic; Combined forecasting

1 Introduction

At present, economic development is facing many risks and challenges, macroeconomic and financial data statistics are different at different times, the frequency of data contained is different, and its advantages are also different, and it is of great practical significance to predict the macroeconomy with scientific theories and reasonable econometric models, provide data reference for decision makers and analyze future economic development. For example, the statistical frequency of macroeconomic data is low, mostly including monthly/quarterly/annual frequency data, and its data has strong stability; The frequency of financial data statistics is relatively high, mostly including daily/hourly frequency data, and its data information is more. How to balance the advantages of macroeconomic data and financial data, and make full use of the original information of data, is the first major problem facing macroeconomic forecasting. The economic situation is complex and changeable, financial market volatility has intensified, and the role of financial market conditions in the assessment of economic situation

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has become more prominent. In the context of big data, tens of thousands of financial data have a huge impact on the macroeconomy, and how to extract useful macroeconomic forecast information from the huge high-frequency financial data is the second major problem at present. This paper uses the mixed frequency data sampling model (MIDAS) to process different frequency data in macroeconomic data and financial data, and reduces the dimensionality of high-frequency data to verify the accuracy of different combined forecasting models on macroeconomic forecasting, and provide reference for decision-makers.

Ghysels et al. (2004) first proposed the MIDAS model, which uses the advantages of the MIDAS model to extract data information of different frequencies to make accurate predictions. Some scholars [1-3] combine the advantages of large amount of information and high frequency contained in financial data with the advantages of MIDAS models in processing data of different frequencies to make real-time predictions of macroeconomic variables. Among them, Bai et al. [3] verified the good prediction effect of the MIDAS model by comparing the accuracy of US GDP prediction with the state space model.This paper verifies the advantages of the MIDAS model in processing different frequency data by combing the existing research results and comparing different prediction models with the MIDAS model, but these studies do not solve the problem of how to deal with most of the information of high-frequency financial data, nor do they mention the contribution of leading financial data to macroeconomic forecasting [4].

In this paper, a mixed frequency data sampling model (MIDAS) is constructed by using daily financial data and monthly/quarterly macroeconomic data, and financial and economic leading factors are added to compare the macroeconomic prediction accuracy of four types of combined forecasting models.

In order to deal with the problem of high-dimensional cross-sectional data of financial variables, this paper adopts the following three methods: (1) financial data is divided into five categories: commodities, corporate risk, stocks, government bonds and foreign exchange rates; (2) In order to reduce the cross-sectional dimension of daily financial data, the principal component analysis method is used to extract public financial factors from the cross-sections of 210 daily financial data, representing the above five types of daily financial data information: (3) Daily financial factors and monthly/quarterly macroeconomic factors are predicted by combined forecasting method, and a large amount of original forecast information contained in daily financial data is mined to improve the accuracy of forecasting.

2 Introduction to the MIDAS model Section Headings

2.1 MIDAS model

The expression of Traditional distribution lag model ADL $\left(p_Y^Q, q_X^Q\right)$ is as follows:

$$Y_{t+1}^Q = \mu + \sum_{k=0}^{p_Y^Q-1} \rho_K Y_{t-k}^Q + \sum_{k=0}^{q_X^Q-1} \beta_k X_{t-k}^Q + u_{t+1} \tag{1}$$

Where p_Y^Q is the lag term of Y_t^Q and q_X^Q is the lag term of X_t^Q. Extrapolating the above argument to the h-step forward prediction yields to the ADL-MIDAS model $\left(p_Y^Q, q_X^D, h\right)$:

$$Y_{t+h}^{Q,h} = \mu^h + \sum_{j=0}^{p_Y^Q=1} \rho_{j+1}^h Y_{t-j}^Q + \beta^h \sum_{j=0}^{q_X^D=1} \sum_{i=0}^{m-1} w_{i+j*m}^{\theta^h} X_{m-i,t-j}^D + u_{t+h}^h \quad (2)$$

Comparing equation (1) in the traditional distribution lag model ADL with equation (2) in the mixed-data model ADL-MIDAS, we can see that equation (1) in ADL involves a time aggregation sequence. For example, in Equation (1) ADL, in order to make the frequency of the explanatory variable and the explanatory variable the explanatory variable the same frequency, the high-frequency data is weighted and averaged, that is: suggest show the time aggregation sequence; RW is the benchmark model, the prediction result shows the RMSE value of the RW model, and the rest of the prediction results displayed by the model are the ratio of the RMSE value predicted by the model to the RMSE value of the benchmark model, when the value is less than 1, the potential improvement of the model's prediction results to RW is considered.

Among them, the low-frequency data is converted into high-frequency data by $W\left(L^{\frac{1}{M}};\theta\right)$ polynomial, so that the low-frequency data Y_t and high-frequency data $X_{m-i,j}^D$ are processed at the same frequency, finally, we obtained the ADL-MIDAS $\left(p_Y^Q, q_X^D, h\right)$ one-equation prediction model. Here M represents the multiplicity of different frequency data, K is the lag order of the high frequency data which is used to find the weight of the parameterization, and h is the step value of the high frequency data prediction.

2.1.1 Traditional forecasting models and MIDAS models.

Traditional predictive models are built and analyzed assuming that the data in the model is the same frequency.

Traditional predictive models are built and analyzed assuming that the data in the model is the same frequency. Comparing equation (1) in the traditional distribution lag model ADL $\left(p_Y^Q, q_X^Q\right)$ with equation (2) in the mixed-data model ADL-MIDAS $\left(p_Y^Q, q_X^D, h\right)$, we can see that equation (1) in ADL $\left(p_Y^Q, q_X^Q\right)$ involves a time aggregation sequence.

For example, in Equation (1) ADL $\left(p_Y^Q, q_X^Q\right)$ in order to make the frequency of the explanatory variable and the explanatory variable the explanatory variable the same frequency, the high-frequency data is weighted and averaged, that is:

$$X_t^Q = \left(X_{1,t}^D + X_{2,t}^D + \cdots + X_{m,t}^D\right)/m \quad (3)$$

Where , m represents the number of days included in a quarter. Then, in the traditional distribution lag ADL $\left(p_Y^Q, q_X^Q\right)$ model, a weighted method is adopted for X_t^D to get the slope which is β_1 / m .

2.2 MIDAS model with leading terms

As suming that the first quarter is forecast with daily financial data at the end of February, that is, at least 44 trading days (2 months) of daily financial data are required. Represents the jth day to the penultimate of the $t+1$ quarter and is a multiple of the month. For example, when $=2$, there are 44 daily leading entries and 1 daily leading term for .

$X_{m-j,t+1}^D$ represents the jth day to the penultimate of the $t+1$ quarter and J_X^D is a multiple of the month. For example, when $J_X^D = 2$, there are 44 daily leading entries $X_{2m/3,t=1}^D$ and 1 daily leading term for $X_{1,t=1}^D$ The model ADL-MI-DAS $\left(p_Y^Q, q_X^D, J_X^D\right)$ can be materialized：

$$Y_{t=h}^{Q,h} = \mu^h + \sum_{k=0}^{p_Y^Q=1} \rho_k^h Y_{t-k}^Q \left[\sum_{i=\left(3-J_X^D\right)*m/3}^{m-1} \omega_{i-m}^{\theta} X_{m-i,t+1}^D + \sum_{j=0}^{q_X^D-1} \sum_{i=0}^{m-1} \omega_{i+j*m}^{\theta^h} X_{m-i,t-j}^D \right] + \mu_{t+h}^h \quad (4)$$

Currently, there are multiple parameterized methods to define the leading and lagging terms of the MIDAS model. In addition, in Equation (4), the slope β^h can have different variations, and the MIDAS model has different representations when various polynomials are combined.

3 Sources and processing of data

3.1 Data Sources

This paper selects three frequency data of daily financial data and monthly/quarterly macroeconomic data, and the data source is the wind database. Based on data acquisition and indicator selection considerations, explanatory variables are divided into long and short samples. Choosing quarterly real GDP growth rate (2010=100) as the explanatory variable, simulated and compared the out-of-sample real-time forecasts with different combinations of forecasting models for macroeconomic forecasting (see Table 1).

Table 1. Long and short sample estimation and prediction space

	Estimated interval	Prediction interval	The total interval of the sample
Short samples	2010.01.01 to 2015.12.31	2016.01.01 to 2018.6.30	2010.01.01 to 2018.6.30

Long samples	2005.01.01 to 2015.12.31	2016.01.01 to 2018.6.30	2005.01.01 to 2018.6.30

The data selection deadline in this article is the end of June 2018, due to the pseudo-out-of-sample forecast, the final forecast data cannot exceed the second quarter of 2018, otherwise it is not possible to use MSEF for the evaluation of pseudo-out-of-sample forecast, considering that the following H-step forward forecast will be made, so as to set the final forecast deadline for the fourth quarter of 2017. The range concludes with a forecast for the second quarter of 2018. Daily financial data contains a total of 210 long and short sample time series for five types of financial indicators, which is a large cross-sectional data (as shown in Table 2).

Table 2. Number of daily financial data indicators（Unit: pcs）

	Daily commodity metrics	Daily company risk indicators	Daily stock indicator	Daily government bond indicator	Daily foreign exchange rate indicator	Total
Long and short sample	36 6	15 10	4 86	10 16	1 17	66 144
Total	42	25	90	26	18	210

In order to reduce the dimensionality of daily/monthly/quarterly data, the common factors were extracted from the long, short and total sample data, and the macroeconomic forecast was combined, and the prediction accuracy of each model was compared (see Table 3).

Table 3. Monthly/quarterly data includes the number and status of indicators

	Contains metrics	Condition
Monthly data	Short sample, 48 indicators	Goods of Production Order Index, Durable Goods Purchase Order Index, PMI, Non-Manufacturing PMI, Goods of Production Inventory Index, Export Price Index, PPI, CPI
Quarterly data	Short sample, 59 indicators	Urban unemployment rate, per capita disposable income of urban residents, per capita consumption expenditure of urban residents, SME development index, cumulative year-on-year contribution rate of GDP, fixed asset investment price index, consumer confidence index, current income perception index, future income confidence index

3.2 Data Processing

In this paper, the following two steps are processed for each time series data X_t : In the first step, for the original data of most variables, which are proved to be non-stationary by testing, the logarithmic or differential transformation is used to transform them into stationary variables. In the second step, the processed stationary sequence data is normalized for the need to estimate the factors.

4 Combinatorial predictive models

In order to make effective use of large amounts of cross-sectional data, two approaches are adopted. The first method is data dimensionality reduction processing, and the common factor is extracted from the cross-sectional data of daily/month/quarterly frequency; The second method, combined forecasting, combines daily financial data and monthly/quarterly macroeconomic data using the MIDAS model.

4.1 Data dimensionality reduction processing

Factor models have received a lot of attention due to their advantages in handling high-dimensional time series. Currently, Bai et al. [4] use factor models to improve model estimation and prediction. The factors in the factor model are rich in information, and researchers introduce the factors into the traditional model to improve the prediction accuracy. Stock et al. [5] have shown that the combination of factors and traditional models can improve the forecasting effect of low-dimensional time series.

The principal component analysis method is based on the idea of cross-sectional averaging and can handle situations with many variables. For daily/monthly/quarterly data extraction, the information criterion of Bai et al. [4] was used to determine the number of factors. The results are shown in Table 4.

Table 4. The different frequency data include samples and factors

	Financial data	Macroeconomic data	
	Daily factor	Monthly factor	Quarterly factor
Long sample	F-L		
Short sample	F-S	F-E-M	F-E-Q
Total sample	F-A	F-E-M	F-E-Q

When the daily financial factors and monthly/quarterly macroeconomic factors are obtained, and each factor is introduced into the MIDAS model, a type of FADL-MIDAS model including quarterly lag terms with explanatory variables and daily financial factors and monthly/quarterly macroeconomic factors can be obtained:

$$Y_{t+h}^{Q,h} = \mu^h + \sum_{k=0}^{p_Y^Q-1} \rho_k^h Y_{t-k}^Q + \sum_{k=0}^{q_F^Q-1} \alpha_k{}' F_{t-k}^Q + \beta^h \sum_{j=0}^{q_X^D-1} \sum_{i=0}^{m-1} \omega_{i+m*j}^{\theta^h} X_{m-i,t-j}^D + \mu_{t+h}^h \quad (5)$$

Where F^Q is the factor variable used to extend the ADL-MIDAS regression model. Equation (5) introduces the traditional factor model and other regressors into the

MIDAS model, combines the summed factors, and uses this method to project the explanatory variables into the daily financial data.

4.2 Combinatorial Predictive Models

The basic idea of a combined predictive model is to build a prediction model in several different ways using a series of original data that changes over time, and then combine the obtained single predictive model. Combinations of predictions based on different information can be represented as multiple weighted averages of predicted values based on a single information. If the count $Y^{Q,h}_{1,t+h}$ t is the weighted average of the h-step mean at the moment, $\left(\hat{Y}^{Q,h}_{1,t+h},\cdots,Y^{Q,h}_{M,t+h}\right)$it is M predicted values based on a single piece of information[6].

The combined forecast can then be expressed as:

$$\hat{Y}^{Q,h}_{C_M,t+h}=\sum_{i=1}^{M}\omega^{h}_{i,t}\hat{Y}^{Q,h}_{i,t+h} \tag{6}$$

Here $\left(\omega^{h}_{i,t}\cdots\omega^{h}_{M,t}\right)$is the vector of combined weights formed at time t; C_M is a combined prediction for a spatial model or a single set of predictions.

Although there are several methods to estimate the combined weights, in order to measure the advantages and disadvantages of the combined prediction model, this paper uses the RW model (1) to construct a benchmark prediction model, and uses the root mean square error RMSE to measure the prediction accuracy of the model, the smaller the relative root mean square prediction error (rRMSE), the better the model prediction effect, and vice versa.

This paper uses daily/monthly/quarterly data to compare the prediction results of a single forecast model with a combined forecasting model to evaluate the effect of mixed frequency data on China's macroeconomic portfolio forecasting. There are three main steps:

First, the forecasting model is divided into four combined forecasting models, namely, univariate forecasting models, forecasting models with macroeconomic data, forecasting models with financial data, and forecasting models with both macroeconomic and financial data. Forecast in MIDAS models with financial data and in predictive models with both macroeconomic and financial data.

Second, for different prediction models, the data of the leading term is substituted into the MIDAS model prediction to compare the prediction effect, but only the comparison between different combined predictive models. If the data used by the same combined predictive model are different, and the lag order taken by the different data is inconsistent, the comparison of the prediction effect of the two models is invalid. For example, when comparing forecasting models with both macroeconomic and financial data, the FADL-MI-DAS model that substitutes monthly macroeconomic data and the FADL model that substitutes quarterly macroeconomic data predict that the comparison is invalid because the optimal lag order of the two models is different.

The expression for the RW model is: $Y_{t+1}^{Q} = \mu + Y_{t}^{Q} + \mu_{t+1}$

5 Model comparison and empirical evidence

5.1 Comparison of traditional forecasting models and combinatorial forecasting models

This paper substitutes daily financial data into the MIDAS model to test whether high-frequency financial data can help improve the accuracy of macroeconomic forecasting. Table 5 shows the prediction results for different combinations of forecasting models for $h=1$ and $h=2$ for long, short, and total samples.

Table 5. Comparison of rRMSE values predicted by different models

Model prediction	Long sample		Short sample		Total sample	
h value	1	2	1	2	1	2
RW	0.108	0.100	0.108	0.100		
AR	0.185	0.185	0.241	0.260	0.126	0.167
FAR(F-E-M)					0.106	0.121
FAR(F-E-Q)	0.153	0.182	0.138	0.205	0.128	0.149
ADL	0.122	0.138	0.134	0.184	0.101	0.154
ADL-MIDAS (J_X^D = 0)			0.145	0.179	0.183	0.210
			0.149	0.181	0.130	0.135
FADL(F-E-M)			0.146	0.177	0.119	0.123
FADL(F-E-Q)			0.225	0.267	0.205	0.223
FADL-MIDAS (J_X^D = 0) (F-E-M) FADL-MIDAS (J_X^D = 0) (F-E-Q)						

Note: This table shows the rRMSE values relative to the baseline model RW for the Real GDP Growth Rate Forecast combination. Prefixing the model with an \"F\" indicates a factorial model. The estimated intervals for long, short and total samples were 2005:Q1-2015:Q4, 2010:Q1-2015:Q4 and 2010:Q1-2015:Q4, respectively, and the prediction intervals were 2016:Q1+h-2018:Q4-h.

5.2 MIDAS model with leading terms

Table 6 on the next page shows the results of a combined forecasting model that uses leading terms in monthly macroeconomic data and daily financial data. It shows three types of combined predictive models: the first type of model is the ADL-MIDAS model with leading term financial data. $J_X^D = 2$ means that 44 trading days or 2 months of financial data leaders will be used on the last day of the second month of the quarter to forecast the current quarter $h=1$ and $h=2$ steps. The second type of model is a predictive model of macroeconomic and financial data with leading terms, that is, a combination of factor models and ADL-MIDAS. The model includes monthly and quarterly macro-economic data and daily financial data leads. The third type of model is a model of macroeconomic data with leading terms. In the FADL-MIDAS $\left(J_X^M = 1, J_X^D = 0\right)$and FADL-MIDAS $\left(J_X^M = 1, J_X^D = 0\right)$models, there is daily financial data but there is no leading term for daily financial data.

Table 6. Different models with leading terms predict rRMSE value comparison

Model prediction	Long sample		Short sample		Total sample	
h value	1	2	1	2	1	2
ADL-MIDAS $\left(J_X^D = 2\right)$FAR	0.185	0.247	0.181	0.187	0.461	0.514
					0.156	0.203
$\left(J_X^M = 1\right)$FAR$\left(J_X^Q = 1\right)$			0.158	0.185	0.122	0.145
			0.130	0.177	0.182	0.179
FADL-MIDAS $\left(J_X^M = 1, J_X^D = 0\right)$			0.303	0.426	0.130	0.158
FADL-MIDAS $\left(J_X^Q = 1, J_X^D = 1\right)$			0.186	0.193	0.648	0.740
					0.552	0.597
FADL-MIDAS $\left(J_X^M = 1, J_X^D = 2\right)$						
FADL-MIDAS $\left(J_X^Q = 1, J_X^D = 2\right)$						

Note: When $J_X^D = 2$, there are 44 daily leading terms; When $J_X^M = 1$, there corresponds to 1 monthly leading term; When $J_X^Q = 1$, there is 1 quarter lead. As in Table 1, prefixing the model with an "F" indicates a factor model.

From Tables 5 and 6, the following conclusions can be drawn:

First, the predictive model of daily financial data can improve the prediction ability of univariate AR. For example, in the case of long samples, when $h = 1$, the prediction accuracy of the financial factors extracted in the long samples, ADL and ADL-MIDAS models improved by 3.2% and 6.3%, respectively, relative to the AR model. For $h = 2$, the forecasting model of daily financial data also improves the forecasting effect. In the total sample case, ADL and ADL-MIDAS models predict better than AR short-sample models.

Second, in the traditional and MIDAS models, macroeconomic factors (monthly/quarterly factors) improve the prediction accuracy of China's macroeconomy, and quarterly macro factors have better prediction effects than monthly macro factors. In the forecasting model with macroeconomic data, by comparing the total sample of macro monthly/quarterly data with the short-sample prediction effect of the univariate forecasting model AR model, the prediction effect of adding macroeconomic factors is better, and the prediction effect of quarterly macro factors is better than that of monthly macro factors. This is consistent with the conclusions of the US data analyzed by Andreou et al. [3]. Third, FADL and FADL-MIDAS models with both macroeconomic and financial data have no significant improvement in predictive power compared with FAR models. This is inconsistent with the conclusions of the US data analyzed empirically by Andreou et al.[3]. This paper uses the analysis of China's economic data to show that the forecasting ability of monthly/quarterly macroeconomic data is comparable to or even better than the forecasting ability of daily financial data. It shows that China's daily financial data package contains a lot of interference information on the future, which affects the forecast effect of daily financial data on China's macroeconomy.

Fourth, using mixed frequency data to predict the model can improve the prediction accuracy of the model. By comparing the prediction effects of ADL-MIDAS and FADL-MIDAS models relative to the corresponding ADL and FADL models, it is concluded that the use of mixed frequency models has a better macroeconomic forecasting effect. For example, when $h=2$, the FADL-MIDAS forecasting model using monthly macroeconomic data and daily financial data improves the forecast accuracy by 8.7% compared to the monthly FADL model. Fifth, when making advance forecasts at $h=2$ steps, the combined prediction of the FADL-MIDAS forecasting model combining daily financial factors and monthly macroeconomic factors outperforms the ADL-MIDAS forecasting model with financial data. For example, in the total sample analysis, when $h=2$, the combined prediction of the FADL-MIDAS prediction model using daily financial factors only improved the prediction accuracy of the ADL-MIDAS model with financial data by only 3.1%.

Sixth, the prediction effect of the model FADL-MIDAS $\left(J_X^Q=1, J_X^D=0\right)$ which has a leading item in quarterly macroeconomic data is better. The FADL-MIDAS model using monthly/quarterly macroeconomic data outperforms the ADL-MIDAS forecast model with only leading items.

To sum up, it is not difficult to find that the forecasting ability of macroeconomic factors is not significantly improved compared with the prediction ability of financial factors, but when the daily financial factors and macro monthly factors are combined with the MIDAS model, their prediction effect will be greatly improved.

5.3 The effect of the combinatorial forecasting model on macroeconomic fitting.

In order to verify the forecast effect, the traditional forecasting model, the mixed frequency forecasting model and the mixed forecast model of macroeconomic data with leading terms are selected to restore the forecast value of the actual quarterly GDP growth rate, and at the same time compare with the actual quarterly GDP value to show the forecast effect of the mixed data on the macroeconomy, and the forecast results are obtained as shown in Figure 1 and Figure 2.

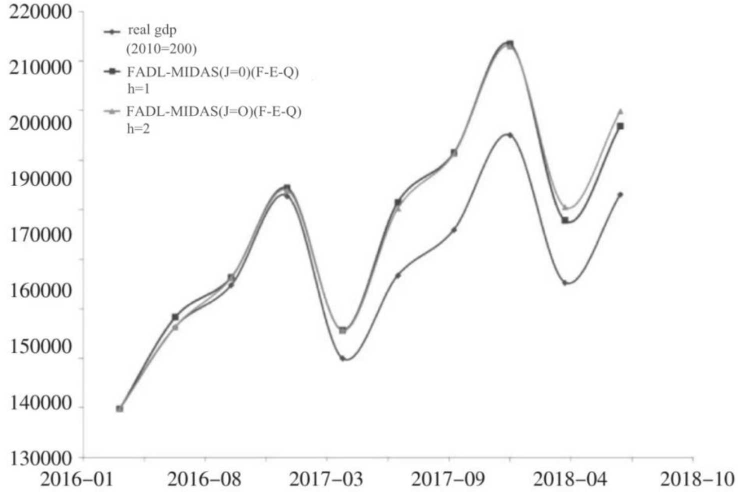

Fig. 1. has both a daily/quarterly data mixing forecast model fitted to real GDP

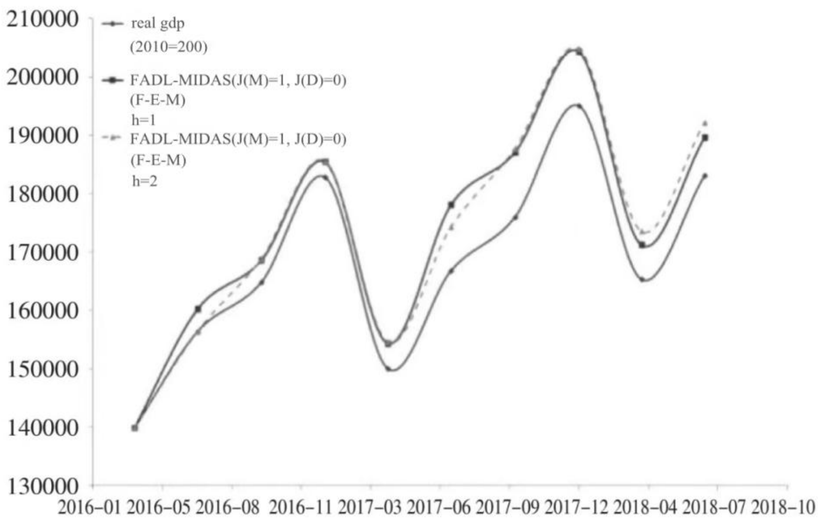

Fig. 2. Fit the monthly data mixing forecast model with leading terms to real GDP

6 Conclusion

In this paper, the combination of daily financial factors and MIDAS model is used to verify the out-of-sample prediction effect of four types of combined forecasting models on macroeconomics, and prove the predictive effect of MIDAS model on macroeconomics by using mixed frequency data. The results show that the MIDAS model significantly improves the accuracy of macroeconomic forecasting through different combinations of daily/monthly/quarterly data forecasting models.

In addition, the MIDAS model with leading term and high-frequency data structure can use rich mixed frequency data information to improve the macroeconomic forecasting effect. When comparing the MIDAS model with the leading items in monthly/quarterly macroeconomic data and daily financial data, it can be concluded that the leading items of monthly/quarterly macroeconomic data have a better macroeconomic forecasting effect than daily financial data. The main problem discussed in this paper is how to use a large number of cross-sectional high-frequency data to improve the prediction of low-frequency series, predicting real GDP growth is only one of the applications of this method, and the forecasting method will also have practical significance in other fields.

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