

Nowcasting and Short-term Forecasting of Chinese Quarterly GDP: Mixed Frequency Approach

Su Zhi-fang, Wang Xiang and He Kai

College of Economics and Finance, Huaqiao University, Fujian Quanzhou 362021, China

KEYWORDS Forecasting. Mixed Data Sampling Model. Mixed Frequency VAR Model

ABSTRACT Conventional macroeconomic forecasting model must change the mixed frequency data into the same frequency data by means of aggregation and interpolation, which ignores the information of high frequency data and decreases the timeliness and accuracy of nowcasting and short-term forecasting. Using monthly and quarterly macroeconomic data, this paper apply mixed data sampling (MIDAS) model and mixed-frequency VAR model (MF-VAR) to nowcast and forecast Chinese quarterly GDP growth rate. The results show that MIDAS model considering an autoregressive item tends to perform better in shorter horizons, whereas MF-VAR model in longer horizons. Additionally, the pooled forecast of MIDAS model and MF-VAR model outperform the individual models. Finally, forecasting results reveal that China's quarterly GDP growth will rebound steadily from the beginning of the third quarter of 2012

1. INTRODUCTION

The US financial crisis since 2008 and the European debt crisis since 2009 have caused a serious impact on China's economy and have smashed the rapid economic growth in China. The expected GDP growth rate of 2012 is 7.5%, according to the state council at the Fifth Session of the Eleventh National People's Congress, which is the first time that the expected GDP growth rate is lower than 8% for eight years. How can China effectively reduce the impact of external shocks on its economic growth and maintain its economic growing stably and rapidly? This requires relevant departments and researchers carry out nowcasting and short-term forecasting China's macroeconomic aggregates accurately and promptly, by using the high-frequency economic data that can reflect the current macroeconomic status and future economic trends, such as the monthly CPI, the industrial value added and the leading indicators etc. Thereby it can provide powerful decision support for the government to implement macro-control policies.

Currently, the quarterly and annually macroeconomic analysis and forecast model, because of its strong foundation of economics and theoretical modeling method and its performance in reflecting our country's economic development and operation regularity, are prevailing for ap-

plying. However, it has three deficiencies as follows: First, due to the annual macro econometric model failure to fully using the high-frequency information at current economic situation, thus it fails to nowcast and short-term forecast the future economic situation timely and accurately; second, with the limitation of sample data volume, the quarterly macroeconomic forecast model based on nonstructural technology often unstable, and adding China's economy having occurred larger structural changes recently, all of this make China's data difficult to apply the nonstructural modeling technology (Research team of the center for macroeconomic research 2007); third, when applying these traditional macro econometric model for forecasting, mixed-frequency data must be converted into the same frequency data, like high-frequency data processing for low-frequency data using aggregation method or alternative method (Silvestrini and Veredas 2008), or translating low-frequency data into high-frequency data adopting interpolation approach (Zhao and Xue 2009), but those two methods exist obviously defects: on the one hand, aggregation method or alternative method missing the high-frequency information and unable to fully use sampling information; on the other hand, although high-frequency data can be obtained by means of interpolation, there exists suspect of artificial construct in that method.

The newly developed mixed-frequency data model can directly use the information of high-frequency data, in the process of converting the high-frequency or low-frequency data into the same frequency data, avoiding the loss of total

Address for correspondence:
Su Zhi-fang
College of Economics and Finance
Huaqiao University, Fujian Quanzhou
362021, China
E-mail: suzufine@hqu.edu.cn

sample information and the rising constructed information and in a position to take advantage of the newest released high-frequency data to amend for the forecast result of low-frequency data, thereby making timely and accurate decision to the potential economic shocks. Mixed-data models have two main models: mixed data sampling (MIDAS) and mixed-frequency vector autoregressive models (mixed-frequency VAR, MF-VAR). MIDAS model proposed by Ghysels et al. (2004), on the basis of the distributed lag model, which is initially used for grabbing out of effective information from high-frequency financial data to predict financial market volatility (Forsberg et al. 2007). Subsequently, Clements and Galvão (2005) apply the MIDAS model and its extensions to the macroeconomic field gradually. In recent years, it has been employed to macroeconomic forecasting increasingly, such as Ribon and Suhoy (2011), based on the daily data from financial market and commodity market, have employed MIDAS model to nowcast and forecast Israel's monthly CPI. And the result shows that the former two weeks within the month can significantly improve the prediction effect of the monthly CPI. MF-VAR model proposed by Zadrozny (1988) is another important mixed-data model, the basic idea is regarding the low-frequency data as high-frequency data with cyclic missing values, and then estimating the state-space representation of MF-VAR by Kalman filter. Kuzin et al. (2009) employs the MF-VAR model to forecast the GDP in EU area, and the research result has discovered that MF-VAR model can nowcast and forecast accurately through taking advantage of mixed-frequency data. Dongho and Schorfheide (2011), based on real-time data, apply the MF-VAR model to forecast US's GDP and compare it with the predicted result of VAR model. And the result shows that MF-VAR model can fully use the monthly data information in quarterly can significantly improve the forecast effect within a relatively short period.

The research and application in domestic on mixed frequency data model is not as common, Xu Jiangang et al. (2007), based on the five minutes high-frequency data of Shanghai composite index and Shenzhen component index, employ MIDAS model and ABDL model to forecast stock market volatility respectively, the results show that the ABDL model in forecasting volatility is better than MIDAS model does. Liu Jinquan and Liu Han (2010) introduce MIDAS model from three aspects as follows: its model theory, its extension and its application, and on this ba-

sis, then testing its feasibility and effectiveness in China's macroscopical economic forecasting using Monte carlo method.

Liu Han and Liu Jinquan (2011) employ the MIDAS model to forecast Chinese quarterly GDP, and the empirical results reveal that the decline in exports is the main factor causing economic growth deceleration in China in the financial crisis, moreover, MIDAS model has a accurate comparative advantage in terms of short-term forecast in Chinese macroeconomic aggregation. There is no doubt that the foregoing research will be of great importance for the application and popularization of mixed-frequency data model in china. However, the researchers also found that the domestic literature do not use the MF-VAR model to predict the quarterly GDP in China, and the comparative study between MIDAS model and MF-VAR model on their predicting performance has not found either. Marcellino and Schumacher (2008) pointed out, theoretically, it is difficult to find out the winner in terms of forecasting performance between MIDAS and MF-VAR, and the relative performance of the two approaches will depend on the underlying unknown data generating process. So, in order to cast about for a suitable mixed-frequency data model for nowcasting and short-term forecasting, it is necessary to apply those two models to forecast, and at the same time finding out which model has better performance by compare their prediction results. In addition, the existed literature mostly employing single indicator models of mixed-frequency data to predict, but these methods have some drawbacks, such as potential model specification error and instability of parameter estimation. And Banerjee and Marcellino (2005), when forecasting the GDP growth rate in Europe area, do not find the existence of the optimal single predicting variable. Therefore, this paper will employ the pooled forecast model to improve the prediction precision in Chinese quarterly GDP growth rate. Pooled forecast model can make full use of the information contained in the variables, and effectively reduces the influence of some random factors in single explanatory variable model.

2. MIXED-FREQUENCY DATA MODEL

2.1 MIDAS Model

The MIDAS approach of h_m -step forward forecast of the individual models is:

$$y_t = \beta_0 + \beta_1 B(L^{1/m}; \theta) x_{t-h_m}^{(m)} + \varepsilon_t^{(m)} \quad \dots\dots 1$$

where y_t is the low-frequency data with $t=1, \dots, T$, and x_t is the high-frequency data with $\tau=1, \dots, mT$. Let $x_t = x_{\tau} \dot{y} m$ is frequency multiple difference of mixed-frequency data, that is, $x_t(m)$ can be expressed that there have m sample from period $t-1$ to period t . The lag operator polynomial $B(L^{1/m}; \theta) = \sum_{k=0}^K \theta B(k, \theta) L^{km}$ that is a weight function of parameter θ . $L^{1/m}$ is the lag operator of high-frequency data, for example, $L^{1/m} x_t^{(m)} = x_{t-1/m}$ and K is the lag order of high-frequency data. The commonly used representation of lag operator polynomials are as follows: Almon polynomial function, exponential Almon polynomial function and Beta polynomial function. Ghysels et al. (2007) believe that exponential Almon polynomial function can construct several of lag polynomial function, this paper therefore select two parameters exponential Almon polynomial weight function to estimate all MIDAS forecasting models, and the parameters of the weight function $\theta_1 \leq 300$ and $\theta_2 \leq 0$. That can not only meet the representation of weight function, required by macroeconomic analysis and forecasting, requirements, but also be able to ensure the positive weight function, and then make the equation having zero approximation error (Ghysels et al. 2006). The specific form of weight function is:

.....2

Given the form of weight function, the parameters in MIDAS model can be estimated using nonlinear least squares (NLS).

Stock and Watson (2003) pointed out that due to economic system has inertia, macroeconomic variables, especially the GDP growth rate, usually exist autocorrelation, it is, therefore, necessary to add a corresponding lag in the model when using explanatory variable to predict GDP growth. So, as an extension to the basic MIDAS, Clements and Galvão (2008) add autoregressive term (AR) in MIDAS model. The AR-MIDAS approach of h_m -step forward forecast of the single indicator model is:

$$y_t = \beta_0 + \lambda y_{t-1} + \beta_1 B(L^{1/m}; \theta) x_{t-h_m}^{(m)} + \varepsilon_t^{(m)} \quad \dots\dots 3$$

2.2 MF-VAR Model

The basic idea of MF-VAR model is, based on time disaggregation, the low frequency data interpolated into unobserved high-frequency data, and then using Kalman filter method to es-

timate the state-space representation of high-frequency data (He et al. 2005). This paper, employing the method of Mariano and Murasawa (2003, 2007), establish the quarterly GDP prediction model of MF-VAR, and the disaggregation of quarterly GDP growth rate into unobserved month-on-month GDP growth is based on the aggregation relation:

$$y_{t_m} = \frac{1}{3} y_{t_m}^* + \frac{2}{3} y_{t_m-1}^* + \frac{2}{3} y_{t_m-2}^* + \frac{1}{3} y_{t_m-3}^* \quad \dots\dots 4$$

which holds for $t_m=3, 6, 9, \dots, T y_m$, because GDP is observed only every third month of each quarter. The above aggregation assumption represents the flow nature of GDP and allows for a linear state-space representation (Mariano and Murasawa 2003). The unobserved month-on-month GDP growth y_{t_m} and the corresponding monthly indicator x_{t_m} are then assumed to follow a bivariate VAR P_{-1} process:

$$\phi(L_m) \begin{pmatrix} y_{t_m}^* - \mu_y^* \\ x_{t_m}^* - \mu_x^* \end{pmatrix} = u_{t_m} \quad \dots\dots 5$$

with $\phi(L_m) = \sum_{k=1}^p \phi_k L_m^k$ and L_m^t and $u_{t_m} \sim N(0, \Sigma)$. To obtain the state-space representation of the MF-VAR, we define the state vector:

$$s_{t_m} = \begin{pmatrix} z_{t_m} \\ \vdots \\ z_{t_m-p} \end{pmatrix}, \quad z_{t_m} = \begin{pmatrix} y_{t_m}^* - \mu_y^* \\ x_{t_m}^* - \mu_x^* \end{pmatrix} \quad \dots\dots 6$$

Since $\sum_{k=0}^{\infty} \exp(-\alpha_k) < \infty$, hence shows that the mean parameters μ_y and μ_x are often quite difficult to estimate in the state-space framework. For this reason, they work with demeaned series for estimation. Transforming (5) into companion form and combining the latter with the aggregation constraint (4), they obtain the corresponding state-space form as

$$s_{t_m+1} = A s_{t_m} + B v_{t_m} \quad \dots\dots 7$$

$$\begin{pmatrix} y_{t_m}^* - \mu_y^* \\ x_{t_m}^* - \mu_x^* \end{pmatrix} = C s_{t_m} \quad \dots\dots 8$$

where $v_{t_m} \sim N(0, I_2)$ and $u_y = 3 u_{t_m}$ hold. The foregoing system matrices are:

$$A = \begin{bmatrix} A_1 \\ A_2 \end{bmatrix}, A_1 = [\phi_1 \dots \phi_p \quad O_{2 \times 2(p-1)}], A_2 = [I_2 \quad O_{2 \times 2}] \quad \dots\dots 9$$

$$B = \begin{bmatrix} \Sigma^{1/2} \\ O_{2 \times 2} \end{bmatrix}, C = [H_0 \dots H_4] \quad \dots\dots 10$$

where matrix C contains the lag polynomial $H(L_m) = \sum_{i=0}^4 H_i L_m^i$ that is defined as:

$$H(L_m) = \begin{bmatrix} 1/3 & 0 \\ 0 & 1 \end{bmatrix} + \begin{bmatrix} 2/3 & 0 \\ 0 & 0 \end{bmatrix} L_m + \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} L_m^2 + \begin{bmatrix} 2/3 & 0 \\ 0 & 0 \end{bmatrix} L_m^3 + \begin{bmatrix} 1/3 & 0 \\ 0 & 0 \end{bmatrix} L_m^4 \quad \dots\dots 11$$

according to the aggregation constraint (4).

To be sure, the researchers apply the Bayesian information criterion (BIC) to determine the lag order of MF-VAR model, and set the maximum lag order of 4 months. The state-space representation (7) and (8) can be estimated by employing the maximum likelihood techniques and expectation maximization (EM) algorithm. After estimation, iterative multi-step forecasts for MF-VAR model can be obtained by iterative Kalman smoother.

3. THE FORECAST PERFORMANCE COMPARISON OF MIXED-FREQUENCY DATA MODEL

3.1 Data

Dataset contains quarterly GDP growth rate and fourteen monthly macro indicators. Specifically, the fourteen monthly indicators are as follows: consumer confidence index (CCI), consumer price index (CPI), retail price index, month-on month changes rate of social retail goods, real estate development comprehensive climate index, month-on month changes rate of industrial added value, month-on month changes rate of fixed-asset investment, month-on month changes rate of M1 and M2, month-on month changes rate of the weighted average interbank interest rate, month-on month changes rate of all loans of financial institutions, month-on month changes rate of leading indicator and total export. Those variables reflect the macroeconomic trend in China from the perspective of consumer consumption, social production and investment, financial market environment and openness to economy etc. The sample period is from 1994M01 to 2012M06. And all of those materials come from China economic informaton network database.

Dataset used in forecasting generally has two forms: one is the final dataset, the other one is real-time dataset. Substantial empirical findings suggest that data revisions do not affect forecast accuracy considerably, and real-time data does either (Bernanke and Boivin 2003; Schumacher and Breitung 2008; Geng and Qi 2012). Additionally, China's National Bureau of Statistics still fails to release authoritative real-time data, this paper therefore employs the final data to forecast rather than uses the former data.

To evaluate the forecast performance of the mixed-frequency data models, the researchers

carry out recursive estimation, nowcasting and "out of sample prediction" in the short run, where the full sample is split into an forecast sample and an estimation sample, which is recursively expanded over time. The forecast sample is between 2004Q3 and 2013Q2, and the estimation sample is between 1994Q1 and 2004Q2. For each forecast sample of GDP growth rate, the researchers want to compute nowcasts and forecasts depending on different monthly information sets. For example, for the initial forecast quarter 2004Q3, the "out of sample" forecasts for GDP growth rate are computed before July 2004, whereas they want to compute a nowcast in July 2004, one in August, and one in September accordingly after the data materials published in July, August and September. Concerning the "out of sample" forecasts, the researchers present results up to two quarters ahead. And then for each forecast sample of GDP growth rate, we have three nowcasts and six "out of sample" forecasts computed based on monthly information available.

3.2 Forecast Performance Comparison

The benchmark forecast model is a simple macroeconomic forecast model for evaluating the performance of mixed-frequency data model. This paper draws on the experience of Kuzin(2009), selecting the in-sample mean model and AR model of quarterly GDP growth as the benchmark forecast, but considering the space, the researchers just present results of the in-sample mean model as the benchmark forecast, and then comparing with other models. The researchers choose MSE (MSFE) to evaluate model's forecast accuracy, and select the well-performing models based on relative MSE (RMSFE), that is, RMSFE is defined as MSFE of forecast model divided by the MSFE of the benchmark forecast. If RMSFE is less than one, the forecast model outperforms its corresponding benchmark forecast.

(1) Performance Comparison Based on the Single Indicator Models

The forecast performance of the benchmark and the single indicator models are listed in Table 1. All the MIDAS and MF-VAR models using single indicator model clearly outperform the benchmark for the nowcast. But it has no com-

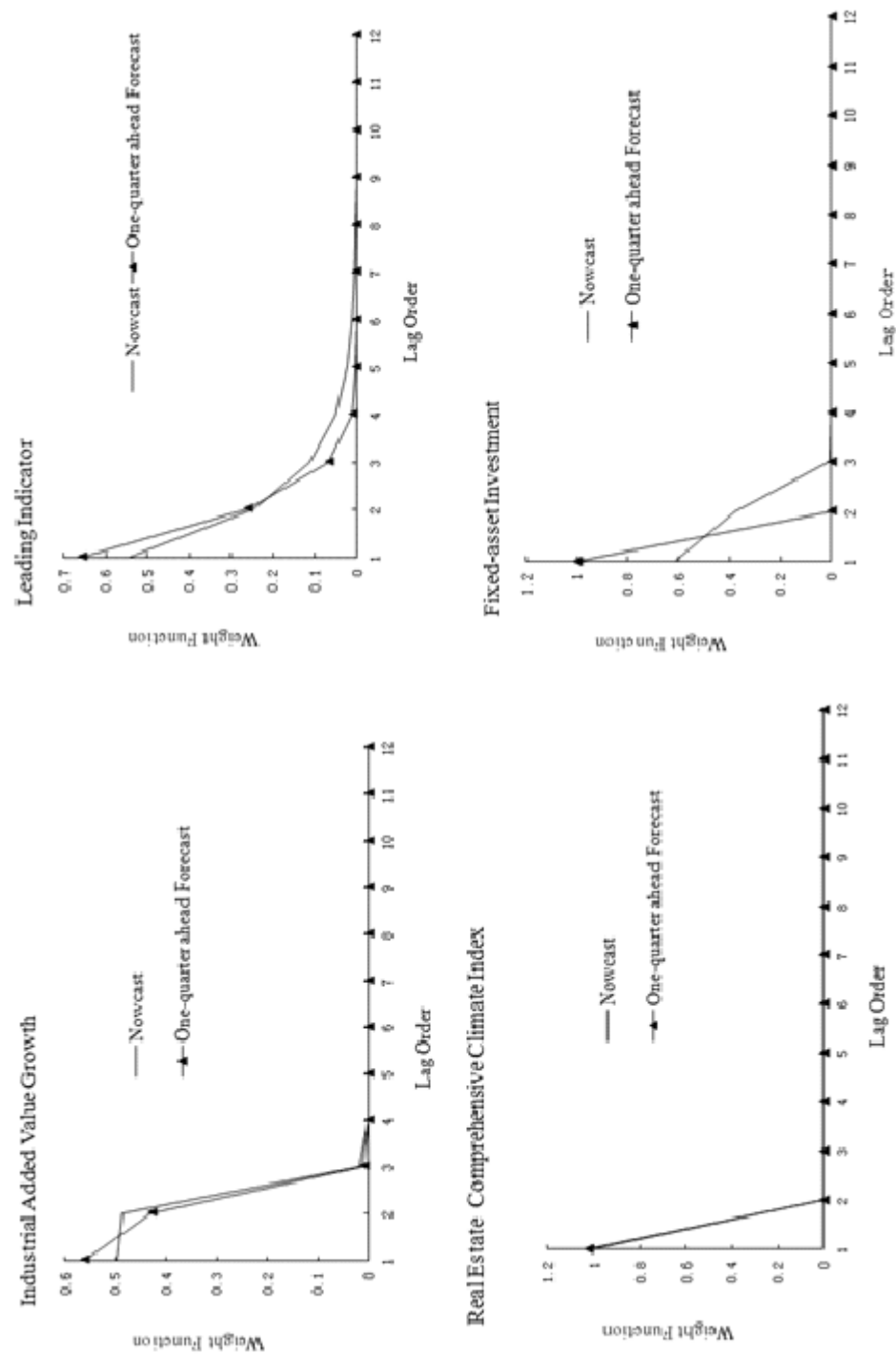


Fig. 1. Weight function for different lag order in AR-MIDAS model

parative advantage in relative long forecast horizon.

Besides, concerning the relative performance between MIDAS and MF-VAR, the researchers cannot identify a clear winner from the results. Because the forecast performance of those two mixed-frequency models relies upon specific variables and forecast horizon, for example, AR-MIDAS model has less RMSFE at short horizon, but at long horizon MF-VAR model does. Moreover, with respect to variables like industrial added value growth, the real estate climate index, the leading indicator and fixed-asset investment, AR-MIDAS model and MF-VAR model outperform than the benchmark in most forecast horizon, which shows these variables are good forecast indicators for predicting China's quarterly GDP.

Figure 1 shows the weight function estimator of four optimal variables in AR-MIDAS model, that is, industrial added value growth, real estate development comprehensive climate index, the leading indicator and fixed-asset investment, in its corresponding lag order. Although the weight function estimator of those four explanatory variables is big from lag order 1 to lag order 4, they decline to zero very soon. This suggests that the volatility of explanatory variables do not have impact on quarterly GDP growth in the long run, we therefore should not choose too many lag orders.

(2) Relative Forecast Performance: MIDAS Model vs. MF-VAR Model

The single indicator model just uses the information in what model has the best forecast performance. And for investigating the relative forecast performance between MIDAS model and MF-VAR model further, the researchers employ the approach proposed by Marcellino et al. (2006), that is, using the information of every variable to compare the relative forecast performance between MIDAS model and MF-VAR model. The first thing is calculating the RMSFE, defined as the MSFE of every mixed-frequency data model via using single explanatory variable model to MSFE of the benchmark. And then, within a model class (MIDAS model, AR-MIDAS model and MF-VAR model), the researchers take the mean of RMSFE of each single explanatory variable model as the indicator to compare forecast performance, and the results listed in Table 2. Both in case of MIDAS model and MF-VAR model,

their RMSFE are bigger than one in horizon $h_m \geq 6$, which indicates that MIDAS model and MF-VAR model are appropriate to forecast in short-term. In horizons at, MF-VAR model outperform than MIDAS model, whereas MIDAS model clearly outperform than the MF-VAR approach at horizon. This is due to the more flexible dynamic specification of MIDAS, which can be particularly helpful at short horizons. Additionally, MIDAS model underperforms than the benchmark in horizon $h_m \geq 7$, while AR-MIDAS model outperforms than the benchmark in horizon $h_m \geq 3$, which suggests that AR-MIDAS model has better performance due to better reflecting the autocorrelation of GDP.

To relate MIDAS and MF-VAR directly, where MF-VAR models serve as benchmark for MIDAS and AR-MIDAS, we compute the relative MSE of MIDAS to MSE of MF-VAR for each single explanatory variable model. And then, within a model class (MIDAS model, AR-MIDAS model), means and medians over all relative MSE are computed, see Table 3. What the researchers can achieve in Table 3 is coherent with Table 2. Specifically, in horizon $h_m \leq 7$, RMSFE of AR-MIDAS model is smaller than one, which indicates AR-MIDAS model outperforms than MF-VAR model at short horizon. However, in horizon $h_m \geq 7$, the MF-VAR approach outperforms than MIDAS model that underperforms than the MF-VAR approach at all horizons.

(3) Forecast Performance Based on the Pooled Forecast Model

Due to the possible presence of model misspecification and parameter instability in single indicator forecast model, Elliott (2006) has proposed the forecast pooling approach to improve the forecast performance of this model. And this result also be confirmed by Banerjee and Marcellino (2005), since the best leading indicators for Euro area GDP growth change over time, and the pooled forecast can protect from this instability. We therefore provide results for the mean, the median, and the weighted mean of the models of the mixed-frequency dataset, where combination weights are obtained from the inverse MSE of the previous four-quarter performance of a model.

Below, we provide the RMSFE of the combinations to the benchmark in Table 4 where we can find that the forecast pooling approach

Table 1: The in-sample forecast performance based on the single indicator models

Variables	Model	Horizon h								
		1	2	3	4	5	6	7	8	9
M2	AR-MIDSA	0.22	0.61	0.59	0.50	0.77	0.80	0.84	1.16	1.18
M1	AR-MIDAS	0.13	0.34	0.36	0.36	0.49	0.77	0.75	1.06	1.11
M1	MF-VAR	0.65	0.90	0.88	0.91	0.96	0.99	0.99	1.09	1.11
Deposits of financial institutions	AR-MIDAS	0.21	0.56	0.58	0.52	0.88	0.93	0.90	1.26	1.06
Leading indicator	MIDAS	0.54	0.61	0.56	0.89	1.00	0.72	1.20	1.22	1.09
Leading indicator	MF-VAR	0.43	0.55	0.55	0.59	0.66	0.75	0.84	0.90	0.96
Leading indicator	AR-MIDAS	0.12	0.27	0.29	0.37	0.56	0.57	0.74	1.17	1.11
The real estate climate index	MF-VAR	0.70	0.77	0.77	0.79	0.82	0.88	0.92	0.97	1.00
The real estate climate index	AR-MIDAS	0.25	0.62	0.67	0.71	1.00	1.12	1.08	1.37	1.39
Industrial added value	MIDAS	0.29	0.41	0.42	0.61	0.86	0.77	1.00	1.10	1.05
Industrial added value	AR-MIDAS	0.10	0.30	0.32	0.45	0.90	0.77	1.07	1.23	1.31
Industrial added value	MF-VAR	0.29	0.36	0.52	0.62	0.69	0.84	0.90	0.92	0.97
Fixed-asset investment	AR-MIDAS	0.23	0.66	0.72	0.59	0.94	0.98	0.96	1.24	1.27
Fixed-asset investment	MF-VAR	0.78	0.97	0.95	0.97	0.98	0.96	0.99	0.99	0.97
CPI	AR-MIDAS	0.21	0.54	0.63	0.70	0.98	1.04	1.07	1.20	1.24
CPI	MF-VAR	0.58	0.76	0.93	0.96	1.04	1.13	1.13	1.15	1.19
interbank interest rate	AR-MIDAS	0.29	0.72	0.66	0.74	1.09	1.14	1.62	1.64	1.59
Total export	AR-MIDAS	0.23	0.57	0.58	0.63	1.03	1.04	1.05	1.39	1.39
Total export	MF-VAR	0.73	0.79	0.87	0.93	0.95	1.03	1.06	1.04	1.07
Consumer expectation index	AR-MIDAS	0.25	0.60	0.67	0.65	1.03	0.99	1.00	1.64	1.87
Consumer expectation index	AR-MIDAS	0.24	0.62	0.63	0.64	1.04	0.98	1.00	1.89	2.00
RPI	AR-MIDAS	0.23	0.57	0.63	0.61	1.00	1.14	1.08	1.27	1.33
RPI	MF-VAR	0.57	0.74	0.90	0.96	1.05	1.14	1.14	1.16	1.20
Social retail goods	AR-MIDAS	0.25	0.72	0.74	0.73	1.11	1.05	1.05	1.48	1.52

Notes: We use the in-sample mean of quarterly GDP growth as benchmark forecast. Only models that outperform the benchmark for are displayed in the table.

Table 2: The average in-sample forecast performance based on the single indicator models

Model	Horizon h								
	1	2	3	4	5	6	7	8	9
MIDAS	0.80	0.90	0.91	1.04	1.11	1.07	1.18	1.24	1.25
AR-MIDAS	0.19	0.50	0.53	0.55	0.87	0.92	0.96	1.32	1.34
MF-VAR	0.63	0.79	0.86	0.91	0.95	1.00	1.03	1.04	1.07

outperforms than the single indicator model because the mean of RMSFE of the combinations to the benchmark in Table 4 is smaller than the single indicator model in Table 2. The RMSFE of the combination of MIDAS and MIDAS-AR to the benchmark of MF-VAR is showed in Table 5, which is coherent with the results in Table 3, that is, AR-MIDAS model outperforms than MF-VAR model at short horizons. Therefore, when predicting the GDP growth in China and we are not certain whether MIDAS or MF-VAR has better forecast performance, we should consider both the forecast result of those two models, and then making a decision from it, specifically, taking the

forecast result of MIDAS at $h=1$, short horizons while taking the forecast of MF-VAR at long horizons.

To investigate the relative performance of the forecast combinations against the individual models, we compute the percentiles of the forecast combinations with respect to all MSE of individual models within a corresponding class, see Table 6. In the case of pooling with weighted means for AR-MIDAS at $=1$, there are 18% individual models within the AR-MIDAS class with smaller MSE than the combination. This suggests that pooled forecast cannot outperform than all of the single indicator models. However,

Table 3: Relative performance: (AR-)MIDAS vs. MF-VAR

MIDAS	Horizon h								
	1	2	3	4	5	6	7	8	9
Mean	1.31	1.15	1.09	1.15	1.17	1.09	1.17	1.22	1.22
Median	1.28	1.13	1.05	1.10	1.14	1.05	1.09	1.17	1.11
AR-MIDAS									
Mean	0.31	0.64	0.63	0.63	0.94	0.93	0.94	1.29	1.29
Median	0.32	0.66	0.64	0.62	0.95	0.92	0.91	1.32	1.29

Note: The MF-VAR model is used as benchmark model. The entries in the tables are obtained as follows: First, in nine horizons, we calculate the RMSFE defined by the MSFE of MIDAS and AR-MIDAS divided by the MSFE of the benchmark. Second, we take means and medians of RMSFE over all models within a model class (MIDAS, AR-MIDAS).

the percentiles of the forecast combinations in table 6 indicate that pooling is a useful alternative to individual models, since a lot of figures in Table 6 are clearly below 30%. In addition, although the forecast combinations against MIDAS perform relatively well, the pooled forecast against AR-MIDAS and MF-VAR does not have great advantage over the individual models. This is because we just have the high-frequency dataset for 14 month. Therefore, if we can add the number of explanatory variables in future research, we believe that the forecast combinations will perform better.

4. THE NOWCAST AND FORECAST FOR QUARTERLY GDP BASED ON THE POOLED FORECAST

The foregoing empirical results indicate that AR-MIDAS model and MF-VAR model clearly

outperform than MIDAS model, as well as the pooled forecast outperforming than the individual models. Based on the newest data available in 2012M6, we employ the pooled AR-MIDAS and the pooled MF-VAR respectively to nowcast the GDP growth in 2012Q3, and then to forecast it in short-term, that is, 2012Q4, 2013Q1 and 2013Q2. The nowcast and forecast results are showed in Table 7 and Table 8. As we can see in Table 7, the nowcast, obtained by AR-MIDAS model, for the quarter-on-quarter GDP growth in 2012Q3 is about 7.8%. This suggests that the economic growth of China is flattening. In addition, the forecast in 2012Q4 and 2013Q1 are 8.2% and 8.5% respectively, which shows that China's economy has been hit bottom in 2012Q3 and will rebound in 2012Q4 and 2013Q1. The reason why the researchers believe the GDP growth of China will recovery after 2012Q3 is that some

Table 4: The RMFSE of the in-sample forecast pooling within a given model class against benchmark

MIDAS	Horizon h								
	1	2	3	4	5	6	7	8	9
Mean	0.74	0.81	0.83	0.91	0.97	0.97	1.05	1.10	1.13
Weighted mean	0.55	0.61	0.65	0.82	0.86	0.89	0.95	0.97	1.03
Median	0.82	0.89	0.93	0.98	1.05	1.03	1.08	1.07	1.08
AR-MIDAS									
Mean	0.17	0.47	0.51	0.54	0.84	0.88	0.91	1.23	1.27
Weighted mean	0.13	0.41	0.45	0.50	0.76	0.77	0.84	1.25	1.16
Median	0.19	0.53	0.57	0.58	0.92	0.96	1.26	1.30	1.33
MF-VAR									
Mean	0.59	0.73	0.80	0.85	0.90	0.96	0.96	0.99	1.01
Weighted mean	0.45	0.58	0.67	0.75	0.81	0.91	0.94	0.96	1.00
Median	0.63	0.82	0.87	0.89	0.96	1.01	1.02	1.04	1.04

Note: The in-sample mean of the quarterly GDP is used as benchmark forecast. And the entries are obtained as follows: First, means, weighted averages and median based on the forecasts obtained by the single indicator model within a given class of models (MIDAS, AR-MIDAS) are computed. Second, we calculate the RMSFE defined by the MSFE of the combination divided by the MSFE of the benchmark.

Table 5: Relative MSE performance: Pooling of (AR-)MIDAS vs. pooling of MF-VAR

MIDAS	Horizon h								
	1	2	3	4	5	6	7	8	9
Mean	1.26	1.11	1.04	1.07	1.09	1.01	1.06	1.10	1.09
Weight mean	1.22	1.06	0.98	1.09	1.06	0.98	1.02	1.03	1.00
Median	1.30	1.09	1.06	1.10	1.09	1.02	1.07	1.03	1.01
AR-MIDAS									
Mean	0.29	0.64	0.64	0.63	0.93	0.91	0.92	1.23	1.22
Weight mean	0.30	0.72	0.67	0.67	0.94	0.85	0.89	1.31	1.16
Median	0.29	0.64	0.66	0.65	0.96	0.95	0.94	1.20	1.21

Note: MF-VAR models serve as benchmark for computing the RMSFE of the combination within a given class (MIDAS and AR-MIDAS). With respect to the calculating steps, see the notes in Table 4.

good news is emerging, that is, the consumer confidence index picks up, the export rebounds and administrative approval procedures of investment projects is accelerating etc. However,

the GDP growth forecast in 2013Q2 may be over-estimated. Because MIDAS model and MF-VAR model are suitable for forecast at short horizons, but at long horizons it is for reference only.

Table 6: The in-sample forecast performance: Pooled forecast model vs. the individual models

MIDAS	Horizon h								
	1	2	3	4	5	6	7	8	9
Mean	0.15	0.16	0.17	0.12	0.09	0.17	0.18	0.29	0.15
Weighted mean	0.11	0.11	0.13	0.09	0.00	0.15	0.00	0.00	0.07
Median	0.17	0.18	0.23	0.16	0.24	0.23	0.28	0.10	0.23
AR-MIDAS									
Mean	0.22	0.23	0.23	0.34	0.22	0.29	0.26	0.37	0.38
Weighted mean	0.18	0.21	0.21	0.27	0.18	0.13	0.17	0.44	0.23
Median	0.23	0.25	0.25	0.38	0.37	0.37	0.32	0.45	0.45
MF-VAR									
Mean	0.25	0.17	0.20	0.21	0.22	0.25	0.25	0.33	0.36
Weighted mean	0.12	0.12	0.15	0.16	0.17	0.20	0.21	0.21	0.31
Median	0.30	0.41	0.28	0.24	0.32	0.43	0.40	0.42	0.40

Note: We implement the pooling exercise as in table 4 and then compute the percentiles of the empirical distribution within the constraints of the RMSFE of individual indicators less than that of pooled forecasts.

Table 7: The nowcast and “out-of-sample” forecast based on the pooled AR-MIDAS

Horizon	Mean				Weight mean				Median			
	2012	2012	2013	2013	2012	2012	2013	2013	2012	2012	2013	2013
	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2
1	7.81	-	-	-	7.84	-	-	-	7.90	-	-	-
2	8.18	-	-	-	7.99	-	-	-	8.25	-	-	-
3	8.27	-	-	-	8.21	-	-	-	8.41	-	-	-
4	8.36	8.25	-	-	7.80	8.25	-	-	8.53	8.25	-	-
5	9.07	8.18	-	-	7.95	8.88	-	-	9.23	8.88	-	-
6	9.04	8.94	-	-	8.75	8.94	-	-	9.07	8.94	-	-
7	9.11	8.84	8.59	-	8.84	8.84	8.59	-	9.16	8.84	8.59	-
8	9.30	10.18	9.67	-	8.60	10.18	9.67	-	9.43	10.18	9.67	-
9	9.34	10.21	9.21	-	8.43	10.21	9.21	-	9.38	10.21	9.21	-
10	9.44	10.24	9.88	9.40	8.49	10.24	9.88	9.40	9.46	10.24	9.88	9.40
11	9.70	10.54	10.43	9.98	8.35	10.54	10.43	9.98	9.70	10.54	10.43	9.98
12	9.84	9.89	9.44	9.34	8.84	9.89	9.44	9.34	9.87	9.89	9.44	9.34

Table 8: The nowcast and “out-of-sample” forecast based on the pooled MF-VAR

Horizon	Mean				eight mean				Median			
	2012	2012	2013	2013	2012	2012	2013	2013	2012	2012	2013	2013
	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2
1	8.89	-	-	-	8.51	-	-	-	9.01	-	-	-
2	9.09	-	-	-	8.66	-	-	-	9.22	-	-	-
3	9.15	-	-	-	8.72	-	-	-	9.26	-	-	-
4	9.37	9.63	-	-	9.05	9.96	-	-	9.60	9.63	-	-
5	9.53	9.74	-	-	9.22	9.74	-	-	9.68	9.74	-	-
6	9.70	9.77	-	-	9.34	9.77	-	-	9.83	9.77	-	-
7	9.83	9.78	9.74	-	9.66	9.78	9.74	-	9.86	9.78	9.74	-
8	9.78	9.82	9.82	-	9.64	9.82	9.82	-	9.91	9.82	9.82	-
9	9.78	9.89	9.85	-	9.63	9.89	9.85	-	9.85	9.89	9.85	-
10	9.84	9.91	9.85	9.82	9.76	9.91	9.85	9.82	9.90	9.91	9.85	9.82
11	9.96	9.95	9.89	9.88	9.88	9.95	9.89	9.88	10.01	9.95	9.89	9.88
12	10.02	10.11	9.94	9.90	9.95	10.11	9.94	9.90	10.09	10.11	9.94	9.90

5. CONCLUSION

In this paper, in terms of the quarterly GDP growth dataset with a set of about fourteen monthly macro indicators, the researchers carry out a recursive forecast comparison exercise between MIDAS model and MF-VAR model, then employing the pooled forecast model to improve the forecast performance. Finally, they nowcast and forecast the quarterly GDP growth of China based on the combination of MIDAS and MIDAS-AR. The main results are the following:

First, when predicting the quarterly GDP growth in China based on MIDAS and MIDAS-AR, we can obtain that, at horizon $h_m \leq 7$, the MIDAS model outperforms than the MF-VAR model, whereas, at horizon $h_m = 8, 9$, the MF-VAR model do much better. Therefore, there seems to be no clear winner in terms of forecasting performance between MIDAS and MF-VAR, the researchers should consider both the forecast result of those two models, and then making a comprehensive decision.

Second, the results show that, based on the combination of MIDAS and MIDAS-AR, the pooled forecast can protect its performance from the misspecification and parameter instability in single indicator models, besides it can clearly outperform than the MIDAS model and the MIDAS-AR model.

Third, the result based on nowcasting and forecasting for China's quarterly GDP growth highlights that its economy will be rebound in 2012Q3 due to the export picking up gradually, consumer confidence index rising significantly

and the fast and stable growing fixed-asset investment. And the quarterly GDP growth forecasts in the following two quarters are 8.2% and 8.5% respectively, which suggests that the economic growth of China will encounter a stable growth period.

ACKNOWLEDGEMENTS

Financial support from the Youth project of National Social Science Fund (11CJY104), Special funding Plan on high level paper and works of Huaqiao University, the project of the human social science on Young Fund of the ministry of Education (10YJC790221), China postdoctoral science funds (2012M510653), Humanities and Social Sciences Class A project of the Education Department of Fujian province (JA12028S) the Program for New Century Excellent Talents in University of Fujian Province (2012FJ-NCET-SK02) and the Cultivation Plan for the Outstanding Young Scientific Talents of Fujian Province's Colleges and universities (11FJJPY04) is gratefully acknowledged. The usual disclaimer applies.

REFERENCES

- Bernanke B, Boivin J 2003. Monetary policy in a data-rich environment. *Journal of Monetary Economics*, 50(3): 525-546.
- Banerjee A, Marcellino M, Masten I 2005. Leading indicators for Euroarea inflation and GDP growth. *Oxford Bulletin of Economics and Statistics*, 67: 785-813.
- Clements MP, Galvão AB 2005. Macroeconomic forecasting with mixed-frequency data: Forecasting US output growth administration. *Warwick Working Paper*.

- Clements MP, Galvão AB 2008. Macroeconomic forecasting with mixed-frequency data: Forecasting output growth in the United States. *Journal of Business and Economic Statistics*, 26(4): 546-554.
- Elliott G, Granger C, Timmermann A 2006. *Handbook of Economic Forecasting*. Holland: Elsevier.
- Forsberg, Lars, Ghysels, Eric 2007. Why do absolute returns predict volatility so well? *Journal of Financial Econometrics*, 5(1): 31-67.
- Ghysels E, Santa-Clara P, Valkanov R 2004. The MIDAS Touch: Mixed Data Sampling Regressions. *CIRANO Working Papers*.
- Ghysels E, Santa-Clara P, Valkanov R 2006. Predicting volatility: How to get most out of returns data sampled at different frequencies. *Journal of Econometrics*, 131: 59-95.
- Ghysels E, Sinko A, Valkanov R 2007. MIDAS regressions: Further results and new directions. *Econometric Reviews*, 26(1): 53-90.
- Geng Peng, Qi Hongqian 2012. Forecasting and assessment of China's quarterly real-time GDP. *Statistical Research*, 1: 8-14.
- He Xinhua, Wu Haiying, Cao Yongfu, Liu Rui 2005. *China's Macroeconomic Quarterly Model China-QEM*. Social Science Academic Press. (China).
- Kuzin V, Marcellino M, Schumacher 2009. MIDAS versus Mixed-Frequency VAR nowcasting GDP in the euro area. *Discussion Paper*, Deutsche Bundesbank.
- Liu Jinquan, Liu Han, Ying Zhong 2010. The application of Chinese macroeconomic mixed-frequency data model. *Economic Science*, 5: 23-34.
- Liu Han, Liu Jinquan 2011. Nowcasting and short-term forecasting of Chinese macroeconomic aggregates. *Economical Research*, 3: 4-17.
- Mariano R, Murasawa Y 2003. A new coincident index of business cycles based on monthly and quarterly series. *Journal of Applied Econometrics*, 18(4): 427-443.
- Marcellino M, Stock J, Watson M 2006. A comparison of direct and iterated multistep AR methods for forecasting macroeconomic time series. *Journal of Econometrics*, 135: 499-526.
- Marcellino M, Schumacher 2008. MIDAS and Dynamic Linear Models. mimeo. Research team of the center for macroeconomic research, Xiamen University 2007. China's quarterly macroeconomic model: development and application. *Journal of Xiamen University (Arts and Social Sciences)*, 4: 28-36.
- Mariano R, Murasawa Y 2007. Constructing a Coincident Index of Business Cycles Without Assuming a One-Factor Model. *Discussion Paper*, College of Economics, Osaka Prefecture University.
- Ribon S, Suhoy T 2011. Forecasting Short Run Inflation Using Mixed Frequency Data. *Working Paper*, Bank of Israel.
- Stock J H, Watson MW 2003. How Did Leading Indicator Forecasts Perform During the 2001 Recession? Federal Reserve Bank of Richmond: *Economic Quarterly*, 89(3): 71-90.
- Schumacher C, Breitung J 2008. Real-time forecasting of German GDP based on a large factor model with monthly and quarterly data. *International Journal of Forecasting*, 3: 368-398.
- Silvestrini A, Veredas D 2008. Temporal aggregation of univariate and multivariate time series models: A survey. *Journal of Economic Surveys*, 22(3): 458-497.
- Schorfheide F, Song D 2011. Real-Time Forecasting with a Mixed Frequency VAR. *Mimeo*, University of Pennsylvania.
- Xu Jiangang, Zhang Xiaorong, Tang Guoxin 2007. Mixed data sampling volatility model. *The Journal of Quantitative and Technical Economics*, 11: 77-85.
- Zadrozny PA 1988. Gaussian-Likelihood of continuous time AR-MAX models when data are stocks and flows at different frequencies. *Econometric Theory*, 4(1): 108-124.
- Zhao Jinwen, Xue Yan 2009. The indirect accounting for China's quarterly GDP. *Statistical Research*, 10: 25-32.