

Retraction

Retracted: Macroeconomic Forecasting Based on Mixed Frequency Vector Autoregression and Neural Network Models

Wireless Communications and Mobile Computing

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] F. Cheng and Z. Fu, "Macroeconomic Forecasting Based on Mixed Frequency Vector Autoregression and Neural Network Models," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 2956289, 12 pages, 2022.

Research Article

Macroeconomic Forecasting Based on Mixed Frequency Vector Autoregression and Neural Network Models

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Macroeconomic indicators include gross domestic product (GDP), consumer price index (CPI), and retail price index (RPI). These indicators are important for understanding the macroeconomic situation and controlling the macroeconomic trend, as they provide a macroscopic view of a country or region's economic performance. If macroeconomic indicators can be predicted accurately in advance, the government and relevant macroeconomic control departments can propose more forward-looking and targeted macroeconomic control policies and deploy the necessary control measures. In addition, individuals can make more reasonable decisions on their investments and savings if they know the macroeconomic indexes in advance. From these two aspects, prediction of macroeconomic indexes is of great research significance. In this paper, we propose a prediction model based on chaotic vector autoregression and neural networks for macroeconomic forecasting, and we model and test the prediction with GDP and inflation as the main concerns, and we find that the improvement of GDP forecasting shows an increase of expected inflation rate, indicating the usefulness of using expected GDP data.

1. Introduction

This paper analyzes the relationship between various macroeconomic forecasting measures, including forecasting inflation rates. The analysis of “forecasting” is particularly advanced in the context of inflation rates. This is because the Phillips curve describing the macroeconomy has been debated on the issue of forecasting inflation rates, and now, the new Keynesian Phillips curve incorporating forecasts of inflation rates occupies the standard position, at least in theory [1].

In practice, the bank came out with quantitative easing (QQE), and the relationship between forecast inflation and monetary policy has become a focus of attention. This monetary policy “is aimed at achieving the ‘price stability target’ of a 2% year-on-year consumer price growth rate as soon as possible, taking into account a time horizon of about two years” and is explicitly designed to influence monetary policy on the forecast inflation rate [2].

When it comes to economic analysis, the analysis of forecast variables is limited to forecasting inflation rates. On the other hand, the government and many economists form and publish GDP forecasts. Various economic activities are often based on these forecasts. For example, the Cabinet Office of the Japanese government publishes the Government Economic Outlook in about late January each year [3]. This schedule is said to be due to the need to prepare the government's draft budget for the following year at this time. Here, forecasting tax revenues is particularly necessary, and GDP forecasts are the basic data for such forecasts.

In other words, when understanding the relationship between economic variables, not only the predicted inflation rate but also the “predicted GDP” should be fully taken into account [4]. However, in the empirical analysis of economic fluctuations, these “forecast variables” are often not taken into account. The reason for this is that, as a practical matter, there is not that much data on prediction. The Cabinet Office only started to conduct and publish numerical surveys

on predicting inflation rates to some extent in April 2004, so there is not as much data accumulated as in other countries [5]. Another theoretical point is that many economists have made assumptions about forecast formation, such as rational and adaptive forecasts. By making assumptions about the formation of forecasts, they extract them from the data of realized values.

However, a growing body of survey-based forecast data have been accumulated, and an increasing number of studies have introduced these data into empirical analyses without assuming forecast formation from the data themselves and have conducted economic analyses. Here, as mentioned above, most of the interests are limited to the predicted inflation rate. Therefore, this paper analyzes the impact of forecasted GDP as well as forecasted inflation rates on economic fluctuations.

The paper is structured as follows: Section 2 discusses the scarcity of previous studies on forecasting GDP, while there are many previous studies on forecasting inflation rates. Section 3 discusses the data used in this paper. Section 4 presents the chaotic economics theory and VAR+BP model analysis of the economy using forecast inflation and forecast GDP. Section 5 concludes the paper.

2. Related Work

There have been attempts to interpret the state of economic development using various approaches. In traditional studies, scholars have commonly used GDP to portray the stage of development of a country's economy. The study of predicting GDP was developed through the study of the Phillips curve. In the Phillips curve, a term for predicting GDP was added to the simple relationship between inflation and GDP, bringing it in line with the idea of the natural unemployment rate hypothesis. Subsequently, a number of papers describe how predicted GDP is formed. Special attention is paid to "adaptive forecasting" and "rational forecasting."

In recent years, when analyzing the Phillips curve, reference has often been made to the New Keynesian Phillips curve, which incorporates rational forecasts and takes into account a certain percentage of firm corrections to prices. However, it is often pointed out that although the New Keynesian Phillips curve captures theoretically the behavioral aspects of economic agents when forecasting the future, it does not apply well to the data. To address this point, analyses are often conducted using a hybrid New Keynesian Phillips curve, which in part allows for "adaptive forecasting" in the formation of inflation forecasts. Literature [6] provides an empirical analysis of the New Keynesian Phillips curve that includes predicted GDP. And the estimation results suggest that the duration of past inflation rates is not negligible and that the empirical performance of the New Keynesian Phillips curve is not necessarily good.

Some studies [7, 8] used the series of forecasted GDP data from survey data to demonstrate the Phillips curve. Thus, a "rigid inflation model" was chosen, suggesting that the formation of inflation forecasts may not be rational. The use of survey data paves the way for analyzing the formation of forecasted GDP without making any specific

assumptions about it and paves the way for testing the nature of forecast formation. Among the most readily available survey data on predicted GDP is the Office Consumption Trends Survey. Xie et al. [9] calculate the DI of predicted GDP derived from the response rate, explore the determinants of household predicted GDP using a VAR, and find that exogenous price fluctuations and monetary policy shocks have an effect on predicted GDP. It was found that exogenous price fluctuations and monetary policy shocks have an impact on predicted GDP. Yang et al. [10] use a VAR to analyze the impact of monetary policy and to assess the spillover path of forecast GDP. Here, it is argued that there is an impact through forecast GDP from the monetary base to each variable. Palanisamy et al. [11] also analyze the impact of monetary policy through a VAR and assess the impact of each variable on forecast inflation. However, Alsubari et al. [12] differ in that the monetary base has no significant effect on the forecast inflation rate. Alaminos et al. [13] use QUICK's monthly survey to assess Abe's economic policies. Using the forecast data of interest rate and inflation, they concluded that the predicted GDP is not significant and the effect of monetary policy is limited under the liquidity trap.

The autoregressive algorithm based on chaotic vectors takes full advantage of the mixed frequency data and overcomes the problems associated with too many parameters in the VAR model. Liu et al. [14] applied Gibbs sampling to the VAR model to obtain estimates of VAR coefficients and missing data. Bansode et al. [15] used the VAR model and Granger causality analysis to study the relationship between inflation and economic growth, and the results showed that inflation is one of the factors affecting economic growth. The study of the relationship between fiscal policy and economic growth in China was studied using the VAR model [16], and after comparing the results with the estimation of homogeneous data, it was found that the results estimated using mixed frequency data were better than those estimated using homogeneous data. Xie et al. [17] used a mixed frequency Bayesian vector autoregressive model (VAR) to compare with a Bayesian vector autoregressive model (QF-BVAR) with quarterly data, and the results showed that the VAR predicted better than the QF-BVAR. Algalil and Zambare [18] introduced a VAR model with mixed and irregular data and studied the impact of fiscal policy and monetary policy on economic growth and obtained the conclusion that the forecasting effect of mixed frequency data is better. Havranek and Zeynalov [19] compared the VAR forecasting results with the traditional Bayesian vector autoregression for quarterly data (QF-BVAR) and found that the VAR forecasting effect was 10%-15% better than the QF-BVAR forecasting effect. Al-Azab et al. [20] argued that for Chinese economic data, the VAR model has an advantage over the QF-BVAR model in macroeconomic forecasting and verified the impact of real estate sector investment on China's macroeconomy.

In recent years, as research has deepened, researchers have found that the mix and diversity of products and industries have an important impact on economic growth. Alqahtani et al. [21] used the income level of the exporting

country and the export value of the corresponding product to measure the income level of a single product, the *PRODY* index, and also proposed the *EXPY* index to describe the income level of the country and proved that based on this, it is possible to achieve a forecast for the future economic growth of the country. The product *PRODY* index and the country *EXPY* index are calculated as follows:

$$\begin{aligned} \text{PRODY}_p &= \sum_c \frac{x_{cp}/X_c}{\sum_c (x_{cp}/X_c)}, \\ \text{EXPY}_c &= \sum_p \left(\frac{x_{cp}}{X_c} \right) \text{PRODY}_p, \end{aligned} \quad (1)$$

where *PRODY* represents the level of income associated with product *p*, x_{cp} represents the total exports of country *c* to product *p*, $X_c = \sum_p x_{cp}$ is the total exports of country *c*, and Y_c represents the GDP per capita of country *c*. In fact, the *PRODY* index is a weighted average of the GDP per capita of countries that export a particular product. EXPY_c represents the level of income associated with a country's exports.

Xu and Zhang [22] proposed a new algorithm based on Markov process to quantify the fitness and complexity of countries through coupled nonlinear mappings. Ali et al. [23] further studied and proposed the fitness complexity method (FCM); for countries, the fitness of a country is directly proportional to the complexity of its exported product; for products, the fewer countries exporting that product indicates that this product requires high technological innovation capability, the more complex that product is, and thus, the complexity of the product is inversely proportional to the number of countries exporting the product. The iterative formula for the two is as follows:

$$\left\{ \begin{aligned} \tilde{F}_c^{(n)} &= \sum_p M_{cp} Q_p^{(n-1)} \\ \tilde{Q}_p^{(n)} &= \frac{1}{\sum_c M_{cp} (1/\tilde{F}_c^{(n-1)})} \end{aligned} \right. \rightarrow \left\{ \begin{aligned} F_c^{(n)} &= \frac{\tilde{F}_c^{(n)}}{\langle \tilde{F}_c^{(n)} \rangle_c}, \\ Q_p^{(n)} &= \frac{\tilde{Q}_p^{(n)}}{\langle \tilde{Q}_p^{(n)} \rangle_p}, \end{aligned} \right. \quad (2)$$

where $\tilde{F}_c^{(n)}$ represents the fitness of country *c* after *n* iterations, $\tilde{Q}_p^{(n)}$ represents the complexity of product *p* after *n* iterations, and M_{cp} is the adjacency matrix of the country-product bipartite graph network. For each iteration, $\tilde{F}_c^{(n)}$, $\tilde{Q}_p^{(n)}$ is calculated first and then normalized. The initial state satisfies $\tilde{Q}_p^{(0)} = 1 \forall p$, $\tilde{F}_c^{(0)} = 1 \forall c$.

Although there are many previous macroeconomic analyses on forecasting GDP, as mentioned above, the analysis of GDP forecasts is limited. In [24], they analyzed the GDP forecasts of ESP Forecast, Inc. In [25], they used the GDP forecasts from the Government Economic Outlook and pointed out the upward bias in the forecasts formed by the

government. Both studies are analyses of forecast performance and would not be positioned as studies that analyze the relationship with macroeconomic variables. The predictive effects of "GDP forecasts" and "forecasted GDP" on actual GDP have been analyzed, but few studies have explicitly introduced this variable into macroeconomic analysis.

3. Methodology

In the chaotic economics theory and VAR model of this paper, five variables are used. The chaotic economics theory and VAR model do not depend on specific theoretical variable relationships and are useful for observing and fact-finding relationships between variables. However, if the variables taken here are completely random, it is difficult to find useful developments because there is no policy behind what relationship to find. Therefore, let us look at the hypothesized relationships for the variables used in this paper.

The variables used in this paper are those in the simplest dynamic stochastic general equilibrium model (DSGE model). It is represented by the following equation:

$$\begin{cases} y_t = E_t y_{t+1} - \sigma(r_t - E_t \pi_{t+1}), \\ \pi_t = \beta E_t \pi_{t+1} + \alpha y_t, \\ r_t = \phi_1 (\pi_t - \pi^*) + \phi_2 y_t. \end{cases} \quad (3)$$

y_t is the change in GDP, π_t is the inflation rate, and r_t is the interest rate; E_t is the forecast operator in period *t* and $t\pi^*$ is the target inflation rate. The other symbols are parameters characterizing the changes in this system: the first equation is often referred to as the new IS curve, the second equation is the New Keynesian Phillips curve, and the third equation is the Taylor rule for monetary policy.

This system is forward-looking because it contains forecasts. Usually, for the formation of such forecasts, rational forecasts are assumed, and the data can be analyzed by satisfying cross-sectional conditions, etc.

Then, is it possible to explain economic fluctuations by assigning rational forecasts to realized data? This in itself is a question that needs to be studied. Instead of considering the correspondence between realized and forecasted values of rational forecasts, it is better to consider the data of realized and forecasted values as taking independent fluctuations and derive from the data what kind of relationship can be found between them. Thus, instead of performing macroeconomic analysis based only on realized value data, a better analysis can be performed if forecast data are also used. Such forecast data are also available in the form of "forecasts" and "predictions" from many actors.

In this paper, induced chaotic economics theory and VAR model are considered. On the other hand, a structural chaotic economics theory and VAR model with a contemporaneous variable relationship as a constraint can also be used. In other words, the structural chaotic economics theory and VAR model can consider the contemporaneous relationship in equation (1) and estimate it. However, drawbacks of the structural chaotic economics theory and VAR model can be pointed out, such as the need to consider

contemporaneous intervariable constraints based on identification constraints and the fact that these constraints may be arbitrary.

On the other hand, this paper explicitly uses the forecasts assumed in the model as data by using the forecasts of market participants. In the DSGE model based on equation (1), the forecasts are derived on the assumption of rational forecasts: it shows fluctuations in GDP, inflation, and interest rates based on realized value data and does not take into account the way the forecasts behave. In other words, without assuming rational forecasts, it is not possible to determine a priori whether they behave like in equation (1). The nature of the relationship between these variables must first be determined. This is one of the reasons why this paper uses the induced chaotic economics theory and VAR model.

Structural chaotic economics theory and VAR models also usually assume constraints on the error terms of the induced chaotic economics theory and VAR models from which the variable relationships between contemporaneous variables are estimated. The induced chaotic economics theory and VAR model can be a benchmark model when structural chaotic economics theory and VAR models are assumed, which is another reason for the induced chaotic economics theory and VAR model analysis in this paper.

Figure 1 shows the construction process of the model in this paper.

The error back propagation (BP) method involved is a learning algorithm used to train a multilayer perceptron. Given the training data, the BP method modifies the joint weights between each layer so that the output of the multilayer perceptron matches the training data.

Suppose the input layer has M input signals, the hidden layer has I nodes, and the output layer has p nodes. The input of the input layer is denoted by X_M , the weight between the input layer and the hidden layer is denoted by W_{IP} , and the weight between the hidden layer and the output layer is denoted by W_{IP} . The output of the output layer is denoted by Y_p . During the training of the samples, the input and output of each layer are calculated using

$$\begin{cases} U_I = \sum_{M=1}^{M_{MAX}} W_{MI} X_M, \\ V_I = f(U_I), \\ U_p = \sum_{I=1}^{I_{MAX}} W_{IP} V_I, \\ Y_p = f(U_p). \end{cases} \quad (4)$$

Then, the learning error of the p th neuron in the output layer becomes

$$E_p(N) = D_p(N) - Y_p(N). \quad (5)$$

The error energy of a single neuron is $(1/2)E_{KP}^2(N)$. The error energies of the neurons in the output layer are added together to obtain. The differential energies are summed to obtain

$$E(N) = \frac{1}{2} \sum_{p=1}^{P_{max}} E_{KP}^2. \quad (6)$$

AM- (additional momentum-) BP method is an improved method based on BP, momentum is momentum, it is a method to analyze the minimum value of parameters by physical law method, and the principle of the method is shown in Figure 2.

The AM-BP method considers that the previous weight adjustment amount is partially added to the weight adjustment amount and becomes the weight adjustment amount learned this time, which is the difference from the BP method. The weight adjustment formula is given by

$$\Delta W(N+1) = M_C [W(N) - W(N-1)] - \eta \frac{\partial E(N)}{\partial W(N)}. \quad (7)$$

In equation (7), M_C represents the moment coefficient of increase and N is the number of training. From equation (7), it can be seen that when $M_C = 0$, the training weights are adjusted according to the gradient descent method. The local gradient value becomes smaller when the training weights of the network are close to the local minima of the error surface. The possibility of falling into the local minimum can be avoided by increasing the moments.

4. Experiments

In this section, the time series model of the chaotic VAR-AMBP model is used to analyze the predicted GDP and the impact of the predicted GDP on the economy.

4.1. Prediction Results. GDP is a very important indicator to measure the economic status of a country or region and provides important support for the decision of national economic regulation. In this thesis, the GDP growth rate is used as an example to verify the accuracy and reference value of the chaotic VAR-AMBP model for forecasting macroeconomic data in China.

Figure 3 indicates the prediction results of GDP growth rate by our chaotic VAR-AMBP model. "2020 Q3&Q4" indicates the results of the October 2020 forecast, which, as mentioned earlier, is in the "+0" group and just in time to obtain the Q3 quarterly data, while September 2020 is in the "+2" group and does not have the Q3 quarterly data, so September 2020 needs to forecast the Q3 data, while October 2020 has already obtained the Q3 data, and the forecast is for Q4 data.

As shown in Figure 4, for the second half of 2020, taking "2020 Q1&Q2&Q3" as an example, for the August 2020 point in time, the data for Q2 2020 are already known, and the first-order difference in GDP growth rate is about -1.3%, i.e., the GDP growth rate in Q2 2020 is 1.3% lower than that in Q1 2020. The data for Q3 2020 are unknown at this point, and chaotic VAR-AMBP forecast for the first-order differential of GDP growth in Q3 2020 is about -0.5%. The actual first-order differential of GDP growth rate is the value, which predicts that the rate of decline of the

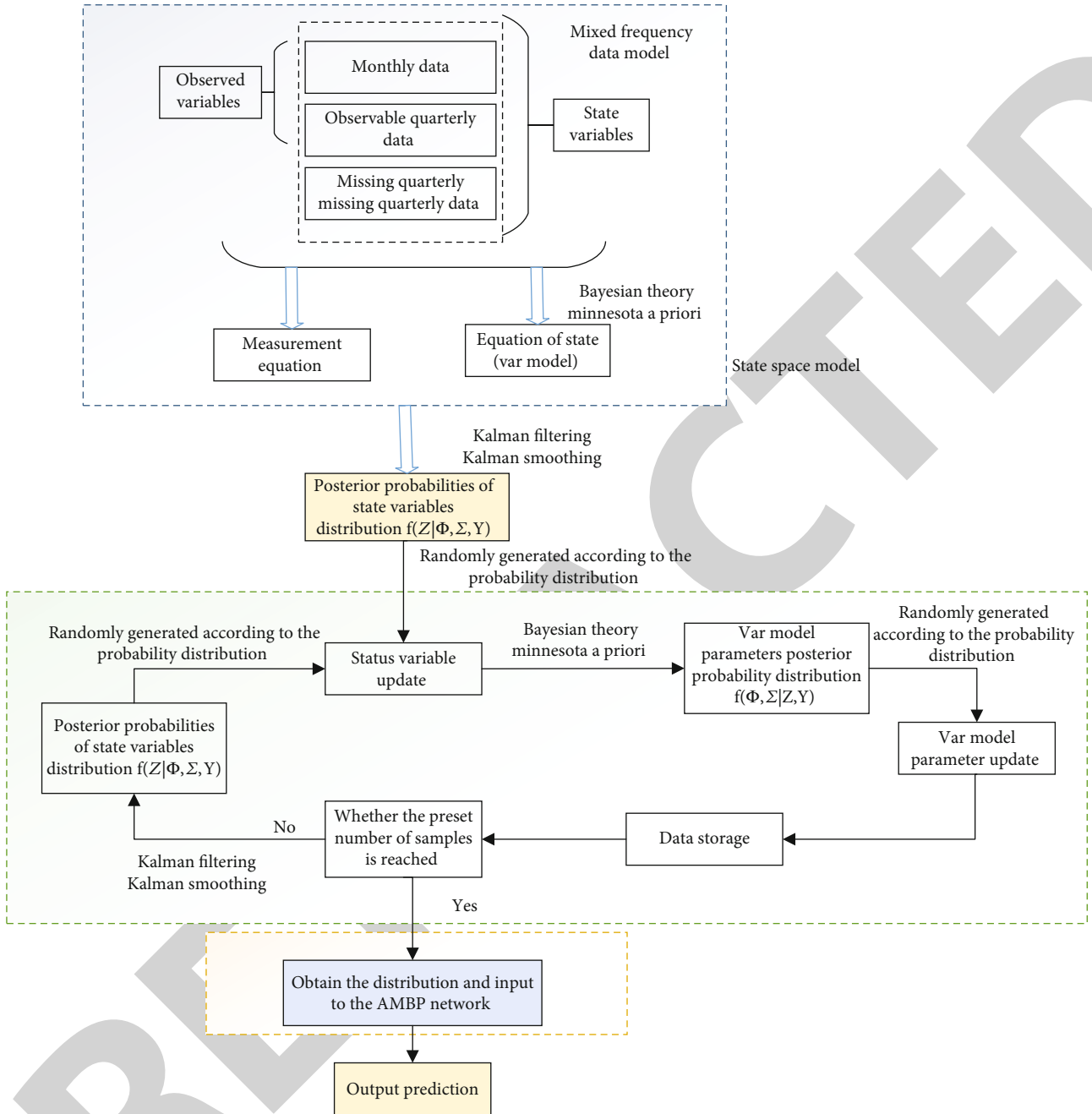


FIGURE 1: Flow chart of model construction.

GDP growth rate in the third quarter of 2020 is much lower than the previous quarter. The chaotic VAR-AMBP model successfully predicts an increase in the first-order differential of GDP growth rate, i.e., a slower rate of decline in GDP growth.

January 2021 is the “+0” group, which has less monthly information for Q1 2021, while February and March 2021 are the “+1” and “+2” groups, respectively. The accuracy of forecasting the change in GDP growth rate in Q1 2021 gradually increases as the monthly information of Q1 2021 increases. The forecast results for April, May, and June 2021 also show that the monthly information within the

quarter can significantly improve the accuracy of the quarterly GDP data forecast, see Figure 5.

From 2020 to 2021, the chaotic VAR-AMBP model predicts the first-order difference of GDP growth rate around 0 and successfully predicts that the GDP growth rate remains basically unchanged, and the Chinese economy enters the “new normal” from then on. Furthermore, the experimental results compared with other methods are shown in Figure 6 and Table 1.

4.2. Stationarity. The variables used in the chaotic economics theory and VAR models are usually required to be

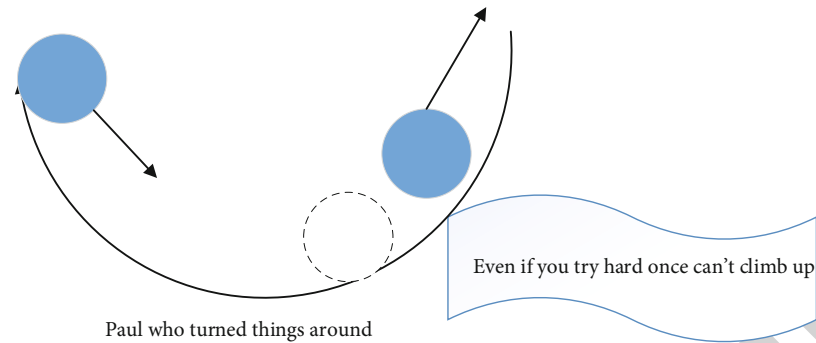


FIGURE 2: Principle of AM-BP method.

stationary. For the six variables used, ADF and DF-GLS tests were performed as unit root tests. For these two variables, only the constant term and the constant and trend terms were tested. Lager utilized the standard Akaike Information Criterion (AIC) as a criterion for model selection. These results are presented in Table 2.

First, in terms of GDP and GDP forecasts, these two tests can deny the zero assumption as the basis of measurement at the level of 1%. In terms of GDP growth rate prediction (CCS), we can reject the zero assumption that the ADF test is 10% and DF-GLS test is 5%. Interest rates, inflation rates, and the projected growth rate of GDP may have different explanations. Neither inflation nor the predicted GDP growth rate (ESP) can refuse 10%, but the DF-GLS test can only refuse a constant of 5%. In terms of interest rates, ADF tests containing trend and constant elements can be rejected at the level of 1%, while DF-GLS tests containing trend and constant elements cannot be rejected even at the level of 10%. However, DF-GLS tests for constant elements only may be rejected by 10%.

Although the results will vary depending on the choice of model, since both GDP and inflation use data such as year-over-year and chain changes and are series that have taken constant differences. This is not unnatural. The forecast GDP and forecast GDP rate series are the results of questionnaires based on GDP and inflation rates, so they can also be considered constant series. The interest rate also fluctuates around 0% and can be considered a constant series given that it is a rate variable representing the return on principal of government bonds. In general, the variables used in this paper are assumed to be $I(0)$ and the analysis will be performed without differencing.

4.3. Granger Causality. The analysis in this paper is based on the chaotic economics theory and VAR model but raises the question of how to arrange the variables in order. Theoretically, the variables should be arranged in the order of exogeneity, but in this paper, as a reference, the Granger causality test is used for the causal relationship between variables. The results of the test are presented in Table 3. The values reported in the table are the statistics under the null hypothesis of “no Granger causality between the two variables.”

First, we can see the relationship from the predicted inflation rate to the actual CPI inflation rate. Next, the rela-

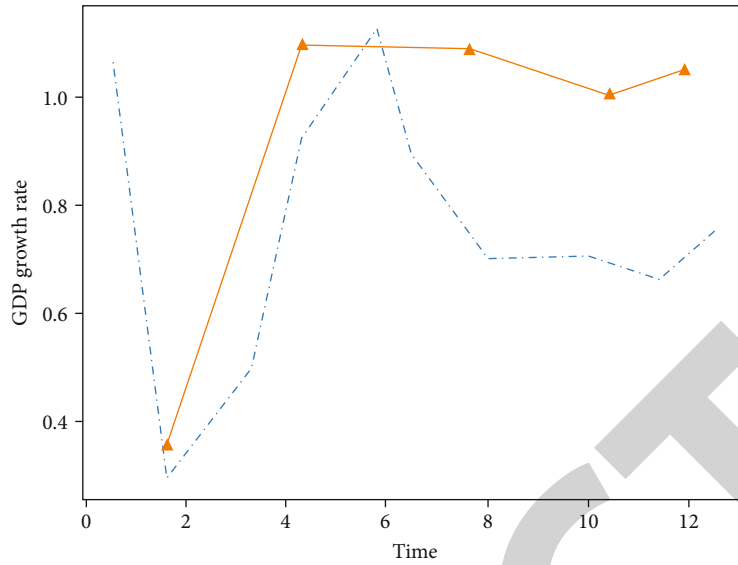
tionship from GDP to the predicted GDP rate is shown. Next, the relationship from GDP to the forecast GDP rate is shown, and finally, the relationship from GDP to interest rates. GDP is the cause of two variables, and the forecasted GDP rate is the cause of one variable. Broadly speaking, the array includes the realized variable set, the forecast variable set, and the forecast GDP rate. The order is roughly in the order of the realized and forecast variable sets, with the order being “GDP, interest rate, inflation rate, forecast GDP rate, forecast GDP.” The analysis is performed in the order of “GDP, interest rate, inflation rate, forecast GDP rate, forecast GDP”.

4.4. Analysis. In this paper, five-variable chaotic economics theory and VAR-AMBP model are estimated. The endogenous variables used in the estimation are the same as those listed, but an exogenous variable is introduced to control for the model: since the consumption tax was increased in April 2021, a dummy variable is included to capture the response to the increase. This also takes into account the jump in the year-over-year change in the CPI, which is considered the inflation rate, during this one-year period due to the tax increase.

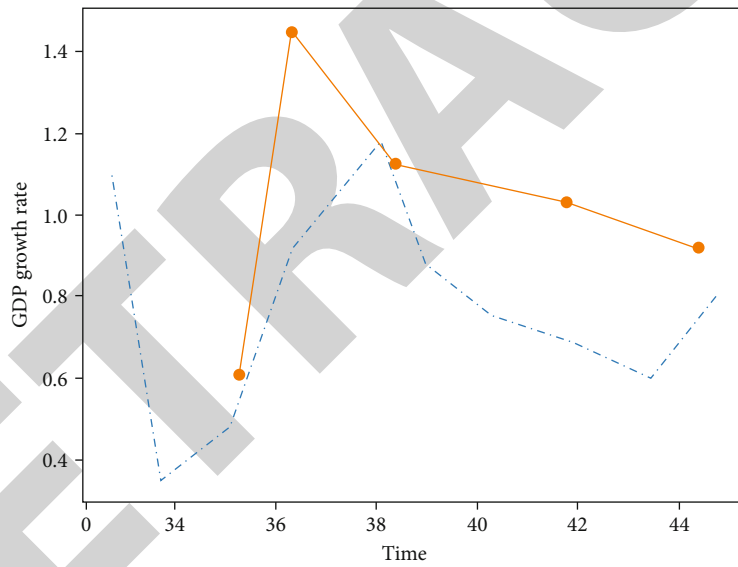
In order to estimate the chaotic economics theory and VAR model, the length of the lag period needs to be determined. The AIC is used here. Lag order 4 was chosen for the model using the “predicted GDP rate (ESP),” and lag order 5 was chosen for the model using the “predicted GDP rate (CCS)” as the data for the predicted GDP rate. Considering that having the same order would be easier to interpret, as well as the fact that fourth-order lags use data from the past year, the model with fourth-order lags was analyzed for both models.

4.5. Discussion. From the above analysis, the following properties of the economy can be considered. First, the forecasted inflation rate has a spillover path that affects realized variables such as GDP and inflation rate. This suggests that the forecasted GDP rate is a variable that has a significant impact on the fluctuations of the economy. This may indicate that the forecast GDP rate is useful as explicit data, which is superior to economic analysis that only follows the inflation rate as a realized value.

The impact of forecasted GDP data on actual and forecasted GDP is also noteworthy, although it is only one



(a) 2020 Q3



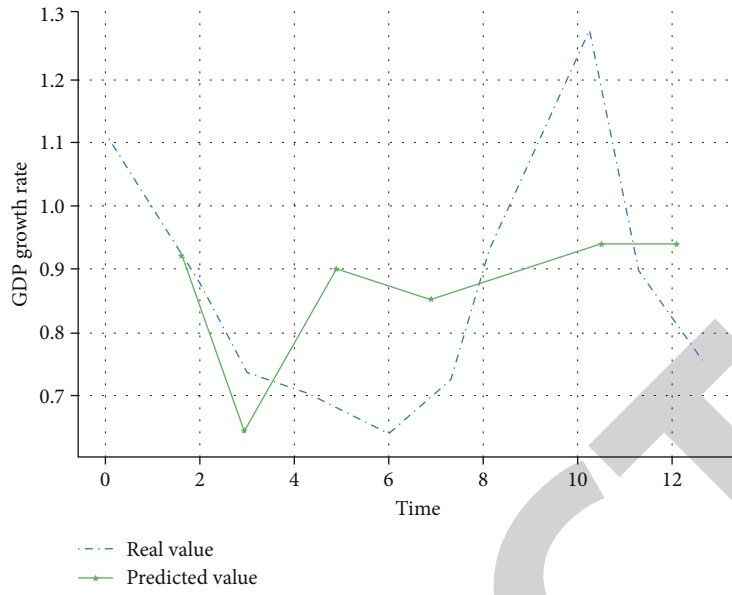
(b) 2020 Q4

FIGURE 3: GDP forecast: 2020.

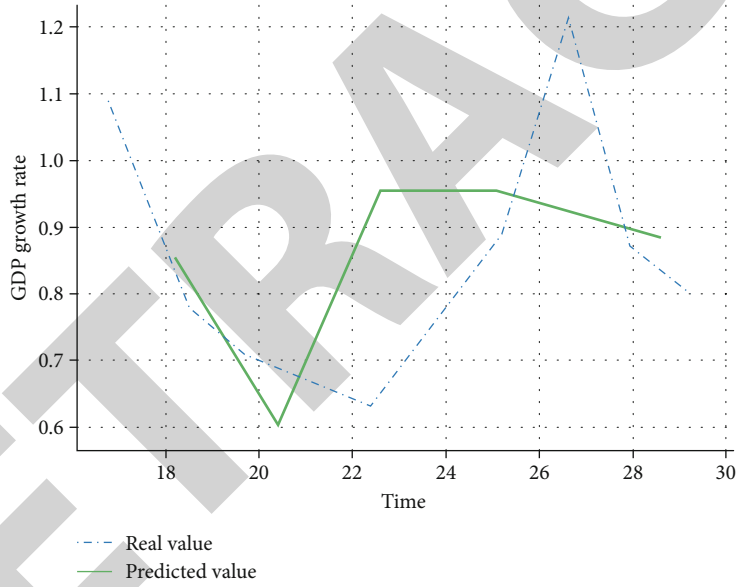
attribute of the analysis using the “forecasted GDP rate” (ESP), as improved forecasts of GDP are shown to lead to higher prices and forecasted GDP rates, illustrating the usefulness of using forecasted GDP data. This will demonstrate the usefulness of using forecasted GDP data.

However, the impact of forecasted GDP on GDP and forecasted GDP is negative. This is not unrelated to the fact that an increase in consumption tax is being discussed during the analysis period. This is because an increase in consumption taxes naturally leads to higher prices, which in turn leads to an increase in the forecasted GDP rate. On

the other hand, it is easy to imagine GDP being suppressed by reducing consumption, and a real decline in GDP in 2014, and a decline in forecast GDP assuming the timing of the tax increase. In particular, in the second half of the data analysis, in December 2011, the April 2014 and October 2015 tax increases were noted; the April 2014 tax increase was implemented, but the November 2014 and October 2015 tax increases were delayed until April 2017. In addition, the May 2016 and April 2017 tax increases were delayed until October 2019. This pressure to raise taxes always makes forecasters aware of price increases that

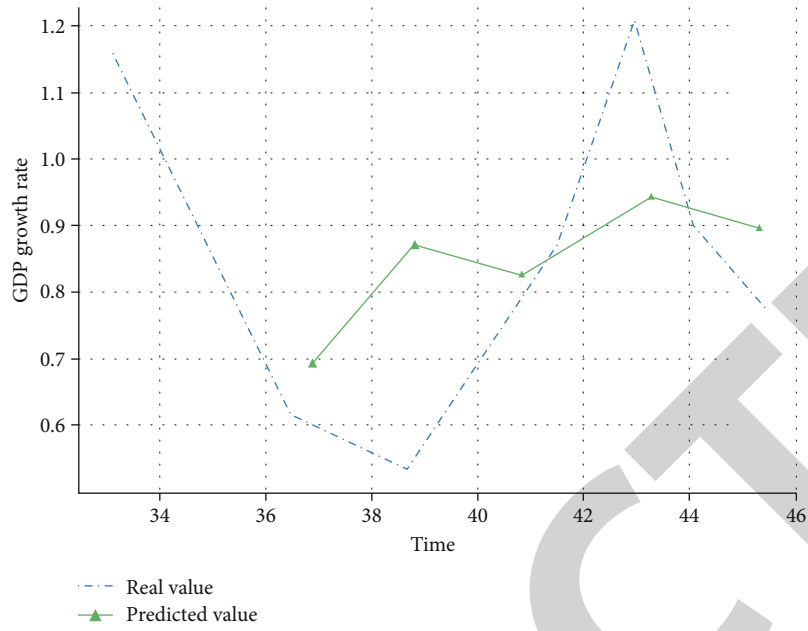


(a) Q1 2020



(b) Q2 2020

FIGURE 4: Continued.



(c) Q3 2020

FIGURE 4: GDP forecast: 2020.

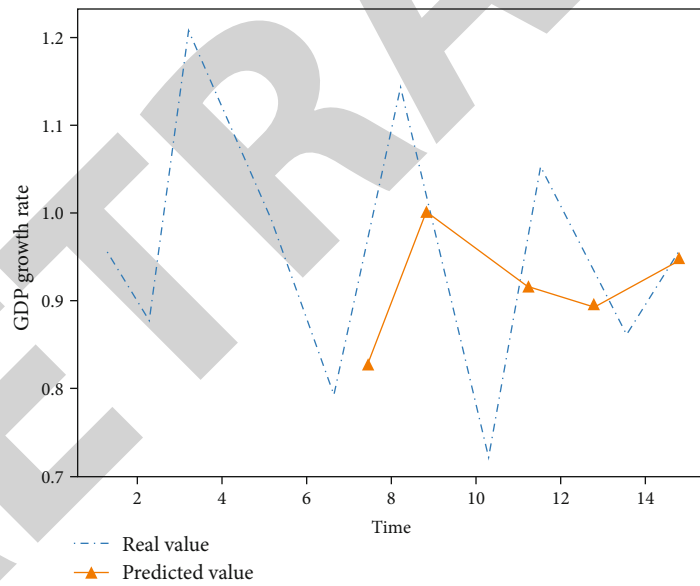


FIGURE 5: GDP forecast: 2021.

depress GDP, which may already be reflected in the forecast inflation data and the forecast GDP data.

The fact that the forecasted GDP rate is positive and significant relative to the inflation rate and the inflation rate is insignificant relative to the forecasted GDP rate may indicate that the economy has acquired the Phillips curve characteristics of New Keynesianism. As the characteristics of the data outlined in Section 3 indicate, the formation of forecasts is quite accurate, which applies to this data analysis, while the formation of forecasts is a follow-up to the realized data, which does not apply from this data analysis. It can be con-

cluded that the forecasted GDP data has, to some extent, the desired characteristics.

GDP shocks have a positive effect on the inflation rate, which also suggests that the data firmly ensure the properties of the Phillips curve. Although a property derived only from analyses using the “forecasted GDP rate” (ESP), GDP shocks also have a positive impact on forecasted GDP, and in this regard, forecasters may be forming their forecasts of GDP by tracking realized data.

With respect to interest rates, the data and analysis in this paper do not show effects on or from other variables.

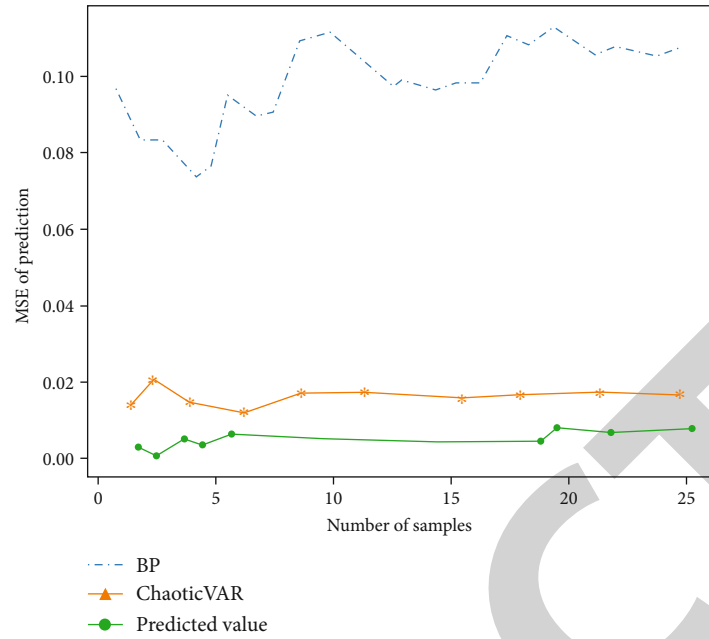


FIGURE 6: Prediction error of the three methods.

TABLE 1: Prediction results of the four types of methods.

Testing method	MSE	Processing time
BP	0.0978	172
AM-BP	0.0961	125
GA-BP	0.0161	107
PCA-GA-BP	0.0062	80

TABLE 2: Unit root tests.

	ADF t value	p value	Lug	DF-GLS t value	Convex mold
GDP	-6.723928	0***	0	-6.708415***	0 intercept
	-6.671349	0***	0	-5.152411***	2 trend and intercept
Interest rate	-1.423378	0.5649	1	-1.792299*	4 intercept
	-4.54325	0.0030***	4	-2.55918	4 trend and intercept
Inflation rate	-2.445669	0.1243	4	-2.230142**	4 intercept
	-2.6089	0.2783	4	-2.662865	4 trend and intercept
Expected inflation rate (ESP)	-2.553282	0.1086	0	-2.365318**	0 intercept
	-2.89675	0.172	0	-2.946275*	0 trend and intercept
Expected inflation rate (CCS)	-2.812696	0.0628*	2	-2.329823**	2 intercept
	-3.306528	0.0756*	2	-3.359099**	2 trend and intercept
Expected GDP	-7.988538	0***	0	-7.857556***	0 intercept
	-8.379598	0***	0	-8.525949***	0 trend and intercept

The right-hand side of the p value in the ADF test and the right-hand side of the t value in the DF-GLS indicate that *significant at 10%, **significant at 5%, and ***significant at 1%.

TABLE 3: Granger causality.

Null hypothesis:	F statistic	Prob.
Expectation of GDP \rightarrow expectation of inflation rate	0.68568	0.5083
Expectation of inflation \rightarrow expectation of GDP	0.54327	0.585
Inflation rate \rightarrow expected inflation rate	0.37355	0.6902
Expected inflation rate \rightarrow inflation rate	9.41744	0.0002***
Interest rate \rightarrow expected inflation rate	1.16585	0.9196
Expected inflation rate \rightarrow interest rate	0.26672	0.7668
GDP \rightarrow expected inflation rate	3.68058	0.033**
Expected inflation rate \rightarrow GDP	1.88862	0.1614
Inflation rate \rightarrow expected GDP	0.32834	0.7215
Expected GDP \rightarrow inflation rate	0.16823	0.7455
Interest rate \rightarrow expected GDP	1.7422	0.186
Expected GDP \rightarrow interest rate	0.34470	0.72
GDP \rightarrow expected GDP	0.10846	0.8975
Expected GDP \rightarrow GDP	0.11055	0.8957
Interest rate \rightarrow inflation rate	1.30939	0.2789
Inflation rate \rightarrow interest rate	0.60376	0.5506
GDP \rightarrow inflation rate	2.20653	0.1204
Inflation rate \rightarrow GDP	1.7553	0.1828
GDP \rightarrow interest rate	4.01932	0.0237**
Interest rate \rightarrow GDP	1.44856	0.2443

On the right side of Prob., **5% significance and ***1% significance.

Even though government bond data are used in this paper, they are not data that would cause significant fluctuations during the analysis period. This may indicate that the information obtained from interest rates on economic fluctuations is heavily influenced.

On the other hand, this paper does not consider the direct effect of economic policies on the variables used in the analysis. Therefore, a separate discussion is needed on how to move the inflation rate and the policy measures that predict it.

5. Conclusion

As noted above, we have highlighted the usefulness of forecasting inflation and forecasting GDP data, but there is considerable room for improvement in these data themselves. In this paper, the main focus has been on simplifying the use of these data, without touching on these improvements. Although it is possible to examine these data in detail with individual data, the relationship with macrovariables is generally absorbed by the constant terms in the individual data. A further issue is the availability of individual data. There is still a long way to improve the accuracy and availability of forecasts, and the analysis using these data has great potential.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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