Research on the deviation between mainstream economic forecasting model and actual economic performance

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Abstract: Economic forecasting has always been an important part of government, enterprises and individuals' decision-making. However, the deviation between the mainstream economic forecasting model and the actual economic performance has always been an important research field. The purpose of this study is to explore the deviations between different types of economic forecasting models and actual economic performance, and to analyze the possible reasons for these deviations. Based on the data of prosperity survey, industrial production and benefit statistics, and considering the inherent periodicity of the economic environment, this paper establishes three economic index forecasting models, namely IS-LM model, CAPM and BP, to forecast and analyze the sales revenue index of industrial products in the fourth quarter of 2020 in J province, and then uses multiple linear regression method to fit several forecasting models to obtain the final combined forecasting model. It is found that all kinds of economic forecasting models show certain forecasting bias in different situations. These deviations are partly due to the limitations of the model itself, including the assumptions, simplification and parameter estimation of the model. In addition, the model may also show shortcomings in predicting external shocks and emergencies, which may lead to deviations. Through empirical research, the combined forecasting model has achieved satisfactory results.

1. Introduction

Economic forecasting has always been an important part of the decision-making of the government, enterprises and individuals. In order to make a wise economic decision, we need reliable economic forecasting models, which can help us predict the future economic trend and make better planning and preparation[1]. However, historically, the deviation between the mainstream economic forecasting model and the actual economic performance has always been an important issue, which has aroused widespread concern and research. This deviation may come from various reasons, including the limitations of the model itself, data quality, external shocks and the complexity of the economic system[2-3]. It is very important to study the nature and causes of these deviations for improving the economic forecasting model and improving the accuracy of decision-making.

The purpose of this paper is to explore the deviation between the mainstream economic forecasting model and the actual economic performance, and analyze the possible reasons for these deviations. We will first review some major economic forecasting models, including traditional macroeconomic models, financial market models and modern machine learning methods. Then, we will compare the forecast results of these models with the actual economic data to evaluate their accuracy and deviation. The goal of this study is to provide economic decision makers, scholars and researchers with in-depth insight into the relationship between economic forecasting models and actual economic performance, thus helping to better understand the limitations and challenges of economic forecasting and how to use these models to guide economic policies and business decisions more effectively.

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2. Review of main economic forecasting models

Economic forecasting refers to the process of trying to predict future economic trends, trends and indicators. These forecasts can be used to guide government policy making, enterprise decision-making and personal financial planning. Economic forecasting is usually based on economic theories and models, as well as historical and current economic data. The main purpose of economic forecasting is to help decision makers, enterprises and individuals make wise economic decisions. These decisions may involve investment, production, consumption, employment, monetary policy, fiscal policy and so on. Economic forecasting is usually based on economic models, which use economic theory to explain economic phenomena. Traditional macroeconomic models, financial market models and machine learning models can all be used for economic forecasting. Economic forecasts can be made for different time ranges, including short-term, medium-term and long-term forecasts. Short-term forecasts usually focus on short-term economic fluctuations, while long-term forecasts pay more attention to structural changes and long-term trends. Economic forecasting is a complex task, which requires comprehensive consideration of various factors and data.

Economic forecasting model is an important tool in the fields of economics and finance, which is used to try to predict future economic trends and trends. Different economic forecasting models adopt different methods and assumptions to cope with the complex economic system. Traditional macroeconomic models, such as IS-LM model, AS-AD model and Phillips curve, are based on a series of macroeconomic relations and equations, and are used to analyze the impact of monetary policy, fiscal policy and inflation on the economy[4-5]. These models are usually based on a set of simplified assumptions, such as stable expectations, full employment, fixed price levels and so on. Nevertheless, they still provide a useful theoretical framework for understanding the macro-economic operation.

Financial market models include Capital Asset Pricing Model (CAPM), Random Walk Theory, Efficient Market Hypothesis, etc. These models focus on analyzing the volatility of capital markets and asset prices in order to predict the performance of stocks, bonds, and other assets[6]. Financial market models are typically based on the rational behavior assumption of market participants, where market prices reflect all available information. However, there are irrational behaviors and information asymmetry in the actual market, and these models may not be able to accurately predict market performance in certain situations.

Modern machine learning methods have been widely used in economic forecasting, including regression analysis, decision tree, neural network and time series analysis[7-8]. These methods can handle a large amount of data, capture nonlinear relationships and adapt to changing market conditions. The machine learning model does not depend on a specific economic theory, but makes predictions through data-driven methods. Their advantage is that they can automatically adapt to new information, but there are also risks of over-fitting and data noise.

Structural models try to deeply understand the interrelationships of various elements in the economic system, so as to better predict economic performance[9]. These models usually include multiple equations and variables to simulate the operation of the economic system. Structural models can be used to evaluate the potential impact of policies, such as the impact of changes in monetary policy or fiscal policy on inflation, employment and output[10]. However, these models usually require a lot of data and complex parameter estimation.

No matter which model is used, economic forecasting is faced with the challenge of uncertainty and deviation. The accuracy of the model depends on the assumptions of the model, the quality of data and the choice of model parameters. In practice, economic forecasting often needs to combine multiple models and expert judgment to obtain more accurate results. With the continuous progress of technology and data, the development of economic forecasting model will continue to evolve to better reflect the economic changes in the real world.

3. Combined forecasting model

The combined economic forecasting model is a method that combines several different economic forecasting models to improve the forecasting accuracy. This method aims to make full use of the advantages of each model and reduce the limitations of a single model. The weighted average method is one of the simplest combination methods, in which the prediction results of multiple models are combined by weighted average[11]. The weights of different models can be determined based on their historical prediction accuracy, professional knowledge, credibility and other factors. This method can reduce the deviation of individual models and improve the accuracy of overall prediction. Singular spectrum analysis is a frequency domain method, which is used to combine multiple time series prediction models. It obtains a comprehensive prediction by Fourier transforming the prediction results of different models and combining them into a frequency domain representation. This method is especially suitable for processing periodic and seasonal data. Multi-model fusion framework is a more advanced method, which combines multiple prediction models, data preprocessing methods and post-processing technologies to construct a complete prediction framework. This method can make full use of the advantages of different models and adapt to different forecasting problems.

Weight distribution can be determined according to model performance, credibility or expert judgment. If there is an n sub-model whose weight is $w_1, w_2, \cdots, w_n$, the sum of weights should be equal to 1, that is, $w_1 + w_2 + \cdots + w_n = 1$.

The weighted average is used to combine the prediction results of different models. If the prediction result of n sub-model is $y_1, y_2, \cdots, y_n$ and the corresponding weight is $w_1, w_2, \cdots, w_n$, then the combined prediction result is $(w_1 * y_1) + (w_2 * y_2) + ... + (w_n * y_n)$.

Based on the data of prosperity survey, industrial production and benefit statistics, and considering the inherent periodicity of the economic environment, this paper establishes three economic index forecasting models, namely IS-LM model, CAPM and BP, to forecast and analyze the sales revenue index of industrial products in the fourth quarter of 2020 in J province, and then uses multiple linear regression method to fit several forecasting models to obtain the final combined forecasting model.

4. Case analysis

Using data mining software and IS-LM model, the development trend of industrial product sales revenue in the fourth quarter of 2020 in J province is predicted. In the fourth quarter of 2020, the industrial product sales revenue will reach 12,102,875 million yuan, up 6.17% year-on-year. Using data mining software and CAPM model to predict the sales revenue of industrial products, the sales revenue of industrial products is 12,287.327 billion yuan, up 7.33% year-on-year. Using MATLAB neural network toolbox and BP neural network model to predict the sales revenue of industrial products, the sales revenue of industrial products is 1,208.371 billion yuan, up 7.72% year-on-year.

Because the above models have their own limitations when forecasting separately, it is not easy to ensure the accuracy of the prediction results, so a combined prediction model is established to predict in order to achieve the complementary effect of the advantages among the models. The multiple linear regression method is used to solve the weight value of each model in the combination forecast, and the sales income of industrial products in the fourth quarter of 2020 is predicted by using the combination forecast model. The sales income of industrial products is 1,223.065 billion yuan, up 5.69% year-on-year.

The prediction results and relative errors of the above four models are compared and analyzed, as shown in Table 1.

From the data in Table 1, it can be seen that the forecast results of various models are compared with the actual data, and the forecast results of the combined forecast model for the sales revenue of industrial products in the fourth quarter of 2020 are significantly improved than those of the single forecast model. Although the performance of CAPM model seems to be slightly better than the combined forecasting model in terms of the sum of squares of errors, the combined forecasting model is obviously better than the other three independent forecasting models because CAPM model only considers the target index itself and does not include the prosperity data and other related indicators in the forecast. The relative error between the combined predicted value and the actual value is very small and within a reasonable range.

Table 1 Prediction results and error values of four prediction models

point of time	Actual value (hundreds of millions)	IS-LM		CAPM		BP		composite pattern	
		predicted value	Error/%	predicted value	Error/%	predicted value	Error/%	predicted value	Error/%
2020.10	93169.046	93001.132	-1.25	92833.919	-1.65	92344.629	-1.94	93120.062	-0.76
2020.11	92413.102	92664.002	1.32	92844.734	1.87	93274.25	1.55	92591.327	0.42
2020.12	92668.55	92925.568	2.06	92928.22	0.96	93156.37	2.24	92747.916	0.29
error sum of squares		12.0325		1.3281		5.54296		1.6028	

5. Conclusions

All kinds of economic forecasting models show certain forecasting deviation in different situations. These deviations are partly due to the limitations of the model itself, including the assumptions, simplification and parameter estimation of the model. In addition, the model may also show shortcomings in predicting external shocks and emergencies. This shows that no general economic forecasting model can completely and accurately capture the complexity of the economic system. The quality and stability of data also play a key role in the accuracy of economic forecasting. Low-quality, inconsistent or lagging data may lead to the deviation of the model, so the improvement of data quality is very important to improve the accuracy of prediction. The combined forecasting model is obviously superior to the single forecasting model. The relative error between the combined predicted value and the actual value is very small and within a reasonable range. On the whole, economic forecasting is a complex task, which needs to consider many factors and uncertainties. Although mainstream economic forecasting models play an important role in providing useful information and guidance, the forecasting results are often restricted by various restrictions and challenges. Therefore, policy makers and economic analysts should use economic forecasts cautiously, and at the same time realize their limitations.

References

[1] Amoroso, N. , Bellantuono, L. , Monaco, A. , Francesco De Nicolò, & Bellotti, R. (2021). Economic interplay forecasting business success. Complexity, 2021(1), 1-12.

[2] Wang, Z. X. , Li, Q. , & Pei, L. L. (2018). A seasonal gm(1,1) model for forecasting the electricity consumption of the primary economic sectors. Energy, 154(1), 522-534.

[3] Llenos, A. L. , & Michael, A. J. (2017). Forecasting the (un)productivity of the 2014 m6.0 south napa aftershock sequence. Ssmological Research Letters, 88(5), 1241-1251.

[4] Min, Z. , & Rui, Q. (2019). Data mining and economic forecasting in dw-based economical decision support system. International journal of reasoning-based intelligent systems, 11(4), 300-307.

[5] Duggan, T. (2018). The cost to build: predictive cost forecasting provides economic edge. Engineering news-record(13), 281.

[6] Gonzalez-Sotres, L. , Frias, P. , & Mateo, C. (2017). Techno-economic assessment of forecasting and communication on centralized voltage control with high pv penetration. Electric Power Systems Research, 151(10), 338-347.

[7] Sen, D. , Gunay, M. E. , & Tunc, K. M. M. (2019). Forecasting annual natural gas consumption using socio-economic indicators for making future policies. Energy, 173(15), 1106-1118.

[8] Juan J. González, Quesada, H. , Adhikari, S. , Bond, B. , & Grushecky, S. (2020). Design of a

total revenue forecasting tool to estimate the economic output of hardwood logs. Forest Products Journal, 70(4), 439-447.

[9] Ellahi, M. , Abbas, G. , Khan, I. , Koola, P. M. , & Farooq, U. (2019). Recent approaches of forecasting and optimal economic dispatch to overcome intermittency of wind and photovoltaic (pv) systems: a review. Energies, 12(22), 4392.

[10] Arif, M. , Liu, Y. , & Haq, I. U. (2019). Load forecasting using neural network integrated with economic dispatch problem. AEU - International Journal of Electronics and Communications, 12(12), 900-905.

[11] Fameliti, S. P. , & Skintzi, V. (2020). Predictive ability and economic gains from volatility forecast combinations. Journal of Forecasting, 39(2), 200-219.