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Research on the Application of Financial Timing Model in Agricultural Product Price Prediction

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Abstract: The Fluctuations in agricultural prices getting more and more attention. Domestic and foreign scholars use the financial timing model to analyze and apply this problem in many aspects. This paper summarizes the research on the financial factors affecting the Fluctuations in agricultural prices and the practical application of the financial timing model in the price prediction of agricultural products.

Keywords: Agricultural products price, Financial factors, Financial timing model.

1. Introduction

The price change of agricultural products is influenced by many different factors. For a long time, the supply and demand relationship and natural factors are considered to be the main causes of agricultural price fluctuations. However, with the research of scholars in recent years, it is found that in addition to some non-financial factors, the influence of financial factors also has a certain relationship with the increasingly prominent financialization trend of agricultural products. And with the continuous study of financial factors, more and more financial time-series models can be used to predict the prices of agricultural products. This review aims to comprehensively summarize the recent literature on the application of financial timing models in agricultural product price prediction to provide a comprehensive understanding of the latest developments in the field. And to explore the remaining problems and future research directions in this field.

2. Financial Factors That Affect the Fluctuations of Agricultural Prices

To realize the price prediction, we must first analyze the impact of financial factors on agricultural prices. Nowadays, many scholars have verified the financial factors affecting the price of agricultural products through financial models.

2.1. Economic Policy Impact

In terms of economic policy, Tian Haosen and Feng Hongjuan (2021) based on SVAR model, considering the impact effect of Chinese monetary policy changes on agricultural prices, the study shows that social financing scale and interest rate will have positive impact on agricultural price index; the changes in the overall price level will further cause the changes of meat and poultry production price index and egg production price index; the changes in social financing scale and interest rate has a significant influence on the producer price index of various agricultural products. Zhang Junhua et al. (2019) studied the effect of policy uncertainty on China's agricultural prices from January 2006 to September 2017 by constructing the factor increasing vector autoregression (FAVAR) model with economic policy uncertainty as the observable potential driving force affecting agricultural prices. It is found that the response of major agricultural prices in China to economic policy uncertainty shocks is significantly real-time, cyclical and negative; it responds to domestic shocks more rapidly and more resilient to international shocks. Ding Zhiguo, Li Boyi (2020) based on the provincial panel data of policy-based agricultural insurance based on the PVAR model to determine the impact of agricultural price fluctuations on policy-based agricultural insurance. It is found that the Fluctuations in agricultural priceshas a promoting effect on the demand of policy-based agricultural insurance, and there is a dynamic interactive effect between the price fluctuation of agricultural products, the farmers' income and the demand of policy-based agricultural insurance.

2.2. External Financial Shocks

In terms of external financial shocks, Cui Chang and Li Guowei (2019) diagnosed the structural turning points included in the sequence of agricultural products price index in China according to the structural change point test method of Bai and Perron,In terms of the external financial shocks, Cui Chang, Li Guowei (2019) diagnosed the structural turning points included in the price index sequence of agricultural products in China according to the structural change point test method of Bai and Perron, Analyzing the causes and attributes of the four turning points in the period from January 1998 to December 2015, from the perspective of supply and demand structure changes, agricultural production cost changes, international agricultural product price changes and policy changes, With the increase of the marketization degree of agricultural products circulation and pricing, The role between production costs, international agricultural prices and money supply and Chinese agricultural prices has also been strengthened, At the same time, the relationship between domestic agricultural prices and other consumer prices has also changed significantly.

2.3. Futures Influence

In terms of the impact of futures, Zhang is hopeful and Li Chongguang (2018) systematically calculated the financialization factors infuencing the spot price of domestic agricultural products in the short term and the ARDL model. The result shows that the domestic futures price is one of the main financialization factors infuencing the spot price of domestic soybean.

2.4. Other Aspects

In other aspects, Peng Hongjun et al. (2019) constructed the Stackelberge game model under the conditional risk value (CVaR) criterion to study the optimal strategy of farmers and companies. The results show that the greater the risk aversion of farmers, the smaller the output of agricultural products, the higher the purchase price made by the company, and the output and purchase price of agricultural products decrease with the increase of the volatility of agricultural products output. Faruk Urak, Abdulbaki Bilgic (2023) used VAR (1) - BEKK-GARCH (1,1) model to study the long-term uncertainty transmission. The results indicate that short-and long-term indirect and direct shocks and long-term uncertainty transmission posing a threat to the product sovereignty and the food security of consumers. At the same time, the asymmetry effect plays a role in the uncertainty of the product market transformation.

3. The Practical Application of Financial Timing Model in Agricultural Product Price Forecast

3.1. ARIMA Class Model

Ding Huijuan et al. (2018) took the Zunyi pork price as an example to analyze the prediction model, constructed the ARIMA model and the gray model, and compared and analyzed the specific steps of the two models. The results show that the ARIMA (1,1,0) model and the grey model GM (1,1) are the optimal prediction model; in the agricultural product price model, the ARIMA model is fit for short-term prediction, and the gray model is propitious for medium and long-term prediction. Cao Shuang, He Yucheng (2015) built based on the wavelet decomposition of SVM-ARI-MA agricultural price prediction model, namely the first wavelet analysis of agricultural price decomposition, extract the four aspects of change trend, and then use SVM model and ARIMA model for the above four change trend analysis and modeling, and reconstruct the combination of agricultural price prediction model. After the example analysis of Chinese cabbage price, it is found that this kind is based on the group of wavelet decomposition. After the example analysis of Chinese cabbage price, it is found that the combined prediction model based on wavelet decomposition has higher prediction accuracy. To improve the accuracy of forestry product sales price prediction, a forestry product sales price forecasting system based on ARIMA and LSTM mixed model is proposed. System design analysis and database design ensure the overall performance of the system. Data quality is improved by preprocessing of historical data. Lu Yao, Chen Wei (2024) used ARIMA model and LSTM residual prediction to make price prediction, and combined the two to obtain the final prediction results. It shows that the prediction error of this system is controlled below 3, which has higher accuracy and strong reliability. Xu Yaqing (2017) for the price prediction of agricultural products, the article has established the exponential smoothing model, ARIMA (sum regression moving average) model and based on the combination of the prediction model, combined with 2011-2015 xi'an rosecarrot market monthly price data, based on the application of the three model SPSS related software for the future short-term carrot price forecast analysis. The results illustrate the combined model is an effective price prediction model for agricultural products.

3.2. The ARCH Class Model

Meng Jun, Lv Xingchen (2021) selected the price sequence of four small agricultural products, garlic, ginger, green onion and mung bean, and analyzed the price fluctuation characteristics by using seasonal adjustment, H-P filtering and ARCH model. The results show that it is seasonal, cyclical and trend, and ginger and scallion have "high risk and high return". Xia Bing (2015) through the ARCH class model for agricultural consumption and agricultural price fluctuations under the background of the agglomeration, the development of the scale trend model validation comparison analysis, and according to the normal distribution characteristics of sample data, combined with the generalized error distribution model validation the final residual value, the results confirmed that the price of agricultural prices have significant generalized ARCH process effect, and the risk of expected consumption of agricultural products yield has a negative impact of 8.1%.

3.3. Deep Learning Model

To improve the accuracy of the graph neural network algorithm adopt empirical modal decomposition method to extract the historical price signals of agricultural products according to the time rotation to extract the features of the historical price signal; decompose the original price signal into multiple intrinsic modal functions and residual items, and construct the sample features according to the characteristic modal function; construct the price prediction graph structure output by the graph structure and output the prediction results through the transition function and the prediction function of the graph neural network. The result shows that the empirical mode decomposition can effectively decompose and extract the components of the intrinsic mode function of the original agricultural price signal, thus reducing the average absolute error of agricultural price prediction of the empirical mode decomposition-graph neural network algorithm by 71.4%. Zhang Dabin et al. (2023) In order to capture the complex traits of futures price fluctuations in the agricultural market and further improve its prediction accuracy, they built a decomposition integration prediction model including variational mode decomposition (VMD) and extreme learning machine (ELM). Taking the futures prices of rice, wheat and soybean meal on CBOT exchange as the research object, the results illustrate that the decomposition integrated prediction model is much better than the single prediction model and provides a new way to predict the price of agricultural futures. Soumik Ray et al. (2023) focused on a machine learning algorithm with special focus on deep learning models. Furthermore, a modified ARIMA-LSTM hybrid model based on the random forest lag selection criterion is proposed. It has been successfully applied to the volatile bean price index. G. Avinash et al. (2024) developed a hidden Markov (HM) -guided deep learning (DL) model for the non-linear and non-stationary price data of agricultural products. HMM models can effectively solve sequence dependencies and hidden states, thus overcoming the lack of generalization ability of HMM models. The proposed method has important prospects for improving the accuracy of the prediction.

3.4. Other Models

Xu Qigang (2014) based on the traditional K nearest neighbor algorithm, according to the characteristics of agricultural price fluctuation in the time series, by calculating

similarity determine the nearest neighbor, using the polynomial function and euclidean distance combination method, and particle swarm optimization algorithm of polynomial function coefficient, K value selection parameter optimization, get improved prediction model. The Experiments show that the improved prediction model has small prediction error and strong prediction stability, and the prediction accuracy can achieve the effect of neural network model. Pei Huiru et al. (2012) showed the results of the relationship between agricultural futures prices and CPI based on vector autoregressive model, information sharing model and state space model that agricultural futures prices can predict the basic trend of CPI 5 months in advance. In the time series prediction problem, it is equally important to extract suitable features and inputs with features that affect the output. Wavelet transform is considered an efficient way to decompose nonstationary signals into uncorrelated components. Sumesh Eratt Parameswaran et al. (2024) cryptocurrency historical data provided through yFinance API and python codes was used as the main data for this work. The results illustrate the model can better predict the trend of cryptocurrency prices. Trend analysis shows whether prices will rise or fall in the coming days. In the future, this work may extend to predict agricultural product prices, changes in climate conditions, and the availability of certain agricultural products (such as Onions) on the market. Zhang Chao and Hou Kai (2019) use B-N technology to decompose the persistent components and temporary components in the price fluctuation of major agricultural products in China, and investigate the inertia of random impact of agricultural products prices.

4. Summary and Outlook

In general, the financial timing model has great potential in analyzing the financial factors of agricultural products, and is widely used in forecasting agricultural products prices, so as to achieve the purpose of reducing costs and increasing benefits. We can also see that under the application of deep learning and machine models, the price prediction is more accurate and the error is smaller, so such models have extremely high prospects and sufficient space for development. The combination of machine learning models or deep learning models with other financial temporal models can significantly improve the prediction accuracy, so this should be the main development direction of scholars in this field in the future.

In addition, some scholars obtain the fluctuation characteristics of specific agricultural products through model processing data, but the conclusions formed only stay at the level of interpretation and description, lacking the research of subsequent application and promotion level. Interpretation and description are only the means and methods of research rather than the purpose, and the ultimate purpose is to intervene and improve. With the deepening of research, it is believed that in the future, more and more attention will be paid to the practical research of financial model in agricultural product price forecast, so as to bring greater optimization and change to the price forecast of agricultural products and other products.

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