Hindawi
Scientific Programming
Volume 2022, Article ID 4572064, 7 pages
https://doi.org/10.1155/2022/4572064

Research Article

Regression Based Price Prediction of Staple Food Materials Using Multivariate Models

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Received 11 April 2022; Revised 12 May 2022; Accepted 23 May 2022; Published 13 June 2022

Academic Editor: Punit Gupta

Profit margins for essential foodstuffs could be a demand rising problem. There are several variables influencing currency fluctuations. For example, the various variables of commodity food prices are climate, crude prices, and so on. Forecasting the fluctuating prices of basic foodstuffs is also relevant even for the government, producers, and customers. The article will use ARCH (autoregressive conditional heteroskedasticity) to forecast the essential food market considering external conditions. The findings agree well enough with the assessment price in the industry by employing two main approaches, ARCH and GARCH (generalized autoregressive conditional heteroskedasticity). For jalapeno, the best result (96.87%) in estimating the cost of employing ARCH is achieved. In the meantime, the best result (99.94%) for the basic food tomato is observed using GARCH. Proportionally, the ARCH is stronger than GARCH, since GARCH is very consistent without disrupting current information.

1. Introduction

Asia has several types of essential foodstuffs. Basic foods get to be an everyday necessity for any people living in the society, particularly in India. The increase and sudden drop in the cost of food staples can thus be a prevalent theme and impact other staple food. References [1, 2] note that rice is the essential and basic food item in India, but there are some other common staple food items in the market as per the Indian Industry and Marketing agents. Those are garlic, coriander, jalapeno, tomato, okra, onion, and carrot.

The positive peak of basic commodity prices in Asia, especially India, has caused everybody concerned and endanger the system's stability. Consistent food prices offer diverse benefits for emerging regions, such as enhancing economic development and avoiding hunger traps [3] for small producers and workers. Consequently, the country would have some procedures to improve fluctuations in the current prices of foodstuffs.

For example, Figure 1 shows directly that from February 2016 through August 2018, the rates of certain essential food products have a similar trend. Prices for all commodities increased from October 2016 to May 2017 in Figure 1. Price fluctuations can be affected by various parameters, including fuel oil prices, climate conditions (snowfall, humidity, and precipitation), political sustainability, exchange rates, and global supply. The forecast of staple food prices may then be perceived to allow the country to settle on the market rate for basic foodstuffs. This study describes the projection of the cost of essential foodstuffs by a plethora of variables including crude prices and climatic conditions. Together with ARCH, one more technique, i.e., GARCH, is used to foresee essential food prices. Such approaches are regarded as strong multivariate predictive tools.

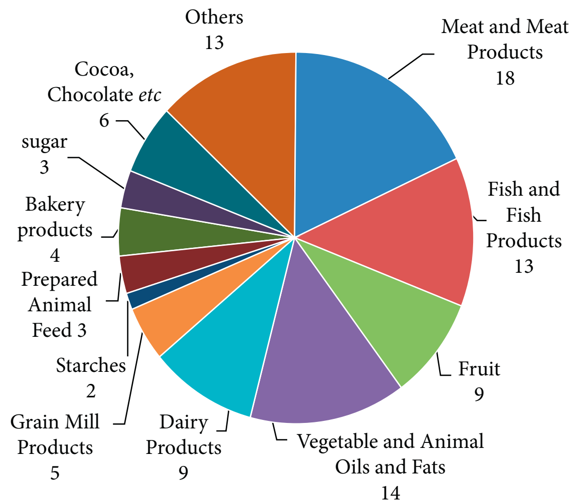

Figure 1: Consumed level food pattern. 2016–18 overall proportion share.

2. Related Works

Widiyaningtyas et al. used Extreme Learning Machine for predicting instability in essential foodstuff price in Indonesia. The average prediction value is 98.79 for all the essential foodstuffs, which is very low [1]. Hasan et al. used Machine Learning approaches for predicting the fluctuating rice prices in Bangladesh. The performance of the Machine Learning model is computed with the 5 styles of information usage levels: 30%, 40%, 50%, 60%, and 70%. Following the implementation of all methods, we observed that the Random Decision Forest dominated all methods, which culminated in 98.17% precision and a usage rate of just 30% [2]. Asnhari et al. studied sudden increase and drop in prices for essential foodstuffs: red chili, onion, garlic, etc. They also studied some external factors like crude oil, political factors, and climatic conditions that cause variations in prices for these staple food materials. They used regression models for the prediction of fluctuating prices of these essential food materials and found that the best results were obtained for red chili staple food as 99.84% using linear regression and for onion as 96.57% using Fourier regression. After performing a rigorous experimental evaluation of these two regression models, they concluded that Fourier regression is a superior model to the linear regression model in predicting the market price of essential foodstuffs [3]. Rosyid et al. used the Exponential Smoothing method for predicting the uncertainties in staple food prices. The method was tested on two levels. The method had got a mean absolute percentage deviation (MAPD) of 3.08% in level 1 and 8.24% in level 2. Finally, they concluded that the model produced an error rate below 10% [4].

Fang et al. used image clustering-based deep learning approach to precisely predict the future price pattern of fruits in China. As demonstrated by the findings obtained, the CNN paradigm is stronger than that of LSTM and LSTM-CNN, while the LSTM-CNN in certain situations produced better results than those of CNN. With the rise in the number of network layers, CNN's output appears to remain consistent [5]. Due to the African plague, the prices of pig meat had got sudden variation in China. Mo and Wen conducted experiments on the available data from the year 2000 to 2019 by proposing a triple phased Markov with a double-layered autoregression model [6]. The indirect consequences of the pork market trend were extensively studied. Their findings revealed the following: (1) Chinese instability of pork prices showed indirect uncertainties, with apparent independent properties in the geographical propagation of pork prices. (2) The system was well suited to shifts in pork prices in China. Chinese swine prices may be split into three divisional mechanisms: "demand decrease," "rate hike," and "accelerated excess demand." (3) Chinese pork price variations in numerous cities have separate degrees of uncertainty, the likelihood for change and period. Mariappan and Ben Das used a crop simulation model to predict rice production based on some external factors like pesticides and fertilizers, climatic conditions, and soil conditions. The results were 4.8 for target value prediction and 0.03 as the mean absolute value [7]. Jain et al. used a decision-making approach for predicting the variations in the opening and closing prices of stock index values. After applying the proposed method to Standard & Poor's 500 and the Dow Jones stock indices, the accuracy achieved was 59.4% [8].

Yaoye et al. considered coal prices as a crucial element influencing electrical prices, considering the monetary gain of power plants as a reference point, first analyzing the conditions influencing coal prices, and then introducing the present pattern of production of power system prices of coal plants in China. Finally, the pre-alarming system for coal-electric connections was developed [9]. In latest years, the market of pork in China has plummeted regularly due to the widespread impact of the African plague and some other aspects. Mo selected the price variation level of all pork-related data between 2000 and 2019. The author utilized versions of GARCH models to examine in each relation the fluctuation and asymmetry of parameters that are dependent on the pork industry. The experimental findings revealed the following: (1) Maize, food, pigs, goats, and swine fluctuate greatly in their price differences. (2) The wheat, food, pigs, and livestock industries will not have a higher degree of risk and yield features whereas the piglet sector has upside potential and yield features. (3) The market variations of grain, piglets, swine, and pork are asymmetrical, in comparison to the price of maize [10]. Yamaguchi and Shirota believed that the fast rise in food pantry consumption contributed to a spike in inventory costs. After the Great East-Japan Earthquake, they used the Random Matrix Theory to predict and analyze varying stock prices of food companies. They derived vectors that are the core elements of time series results [11].

Wang and Wu analyzed pork price uncertainties based on monthly pork market information from 2007 to 2011 in China. Their findings are as follows: (1) Pork's substantial variation is not triggered by pig breeding and circulation costs. (2) Extreme events are mainly due to infectious diseases. (3) The poor pig production association has intensified pork price volatility [12].

Despite the difference in vegetable demand, the impact of consumer welfare improved. Zhao used reimbursement vector model evaluating shifts in low-level and high-level consumer welfare between 1998 and 2013, triggered by vegetable price variation [13]. Anggraeni et al. used an Artificial Neural Network to predict chili price, and the study revealed 16.19% MAPD [14]. Jia and Li used the ARCH model to study the Shanghai stock index as an analytical illustration and examine the impact that the market shift and monetary policy have on the variability of the share price. They stated that monetary policy change has a sustainable net impact on market price fluctuation [15]. Vaishali et al. used Autoregressive Integrated Moving Average (ARIMA) model to carry out Mortgage Refinance Analysis focused on the variability of valuations for homes [16]. Zhang and Chen used the Grey Fuzzy Theory to predict the fluctuating pattern of the consumer price index (CPI) of commodities in China. Furthermore, the work has presented a variety of reasons likely to influence the CPI and stated that the increasing price of food items and residential items is the most significant aspect influencing the CPI [17]. Nagarajan et al. used ARIMA model for price prediction of 41 types of daily essential foodstuffs needed in urban houses like salt, vegetables, vinegar, and garlic. After evaluating the predicted price and actual price, they concluded that the ARIMA models are good in predicting the trend of the market price for essential foodstuffs [18].

Qian et al.'s study confirms the findings of Chinese rice's production, consumption, and inventory from the macroeconomic calculation of fluctuation regarding economic and noneconomic considerations. The principal aim is to define significant parameters of food grain determination and to forecast the production, availability, and exchange of China's rice shortly. The outcome shows that the self-price fluctuation value is 0.046; the labor input fluctuation value is 0.09. Market price fluctuation is −0.115 and −0.140, and production revenue fluctuation is −0.157 and −0.216. The projected outcome indicates that overall demand will have a declining trend, but the total output will have a marginally greater pattern, and Chinese rice's trade balance will continue to increase in the next few years [19]. Asha et al. used ensemble learning approach for the prediction of prices for 17 food products and concluded that the proposed model had achieved an accuracy gain of 10% on average [20].

Many authors, researchers, practitioners, and scholars have performed predictions on staple foodstuffs by employing different techniques like Extreme Learning [21], Artificial Neural Networks [22], Neural Networks [23], Deep Neural Networks, Recurrent Neural Networks [24], Fourier models with ARIMA [3], Exponential Smoothing Method [4], Deep Learning [5], Random Matrix Theory [11], Empirical Analysis [12], Fuzzy Theory [17], ARIMA model [18], LSTM [21], ARIMA + SVR [25], and Triple Exponential Smoothing [26].

It aims to introduce, evaluate, and use regression with ARCH to forecast multivariate pricing for basic food items. Furthermore, in this work, we examined the performance of both models in terms of classification accuracy. Four sections are included in this article after the first section. Section 2 offers a short overview of the ARCH and GARCH for the prediction of basic foods. The approach and findings review are developed in Section 3. Finally, section 5 gives the conclusion.

The main contributions of the work are as follows:

(i) We compare ARCH and GRACH models for price prediction of staple food materials using multivariate models.

(ii) We conclude that the ARCH is stronger than GARCH since GARCH is very consistent without disrupting current information.

(iii) The best result in estimating the cost of employing ARCH is achieved for jalapeno at 96.87%. In the meantime, the best result for the basic food tomato, 99.94%, is observed using GARCH.

3. Methods and Materials

3.1. Data Collection. Food commodity market variations such as regional price, crude oil, and weather information from India were gathered [27]. The information for this analysis will be used from 2015 to 2018. The examples of statistics collected for this study are shown in Table 1. The statistics here were obtained from 23 January 2015 to 27 July 2018 and are split within a week. The cumulative information consists of 4392 rows, containing goods, high price, thermal, and precipitation data for each of the 1098 rows.

3.2. Development and Execution of the Framework. There are certain procedures to do in this study. In Figure 2, this framework's flow mechanism is demonstrated [28]. The very first method is data collection for all factors, such as data on product rates, oil and gas higher price and thermal prices, and annual precipitation from India.

Table 1: Research data used.

Food staple	Date	Cost	High price	Thermal	Precipitation
Jalapeno	24-01-2015	55000	6500	6300	20
	28-01-2015	75000	6500	6300	27
	8-02-2015	45000	6500	6300	24
Allium sativum	24-01-2015	16547	6500	6300	20
	28-01-2015	15476	6500	6300	27
	8-02-2015	15321	6500	6300	24
Green hot pepper	24-01-2015	80000	6500	6300	20
	28-01-2015	80000	6500	6300	27
	8-02-2015	60000	6500	6300	24
Tomato	24-01-2015	50000	6500	6300	20
	28-01-2015	70000	6500	6300	27
	8-02-2015	45000	6500	6300	24
Okra	24-01-2015	48000	6500	6300	20
	28-01-2015	72000	6500	6300	27
	8-02-2015	62000	6500	6300	24
Red hot pepper	24-01-2015	20000	6500	6300	20
	28-01-2015	102810	6500	6300	27
	8-02-2015	93750	6500	6300	24

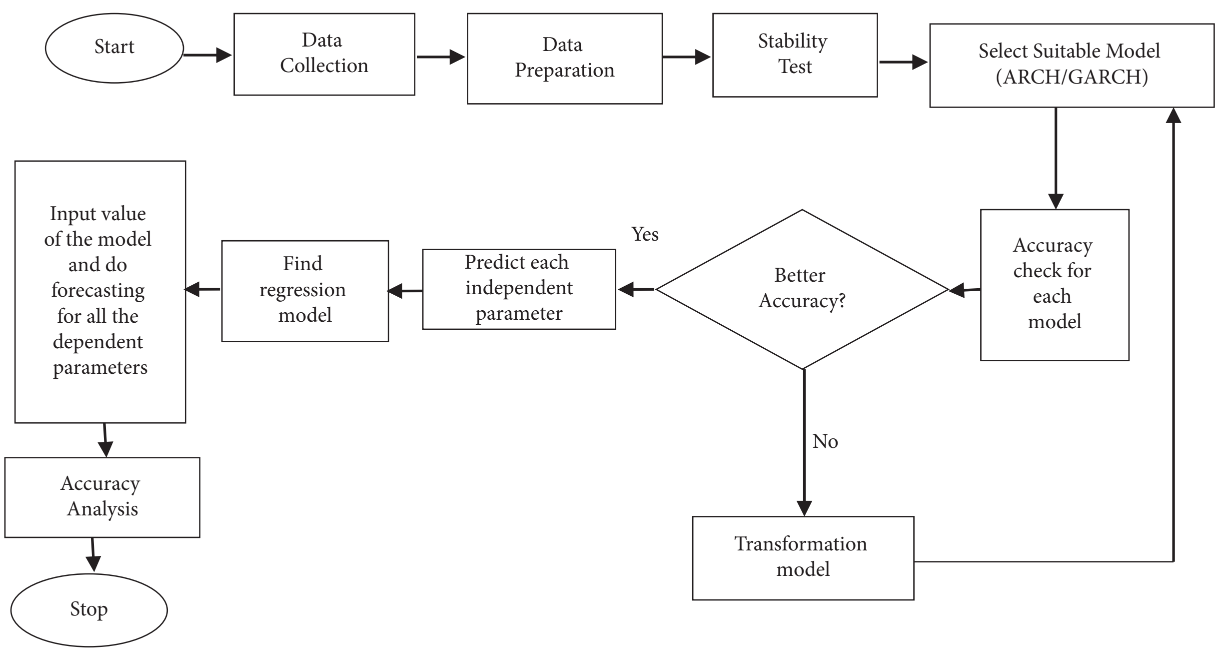

Figure 2: Build of method for forecasting food prices.

4. Results and Discussion

One more phase is data processing; information will be organized in the same timeline of 1 per day as seen in Table 1. Then, in the stationary test phase, there could be no development or decrease in the outcome. Mostly along clock axes, details should be longitudinal. In other terms, number variations are near a fixed mean price, not dependent on perturbation period and variant [29]. The stability test is conducted on all parameters and seems to have a p value <0.05. Stability test outcomes can be used as a reference value for embedded designs. Then, another good ARCH version will be developed. Version recognition is done to analyze data's meaning. Recognizing ARCH models use auto- and partial correlation (ACF) features. Then, each model's consistency is tested [30].

If there are anomalies in given data and the precision of given data is poor, then value change is required using some translation. First, each measurement item will be predicted in this analysis, and the findings would be used to construct an estimation technique for each predictor variable [31]. Step two is to bundle the prediction outcomes of all predictor variables in a feature vector and use this feature vector to find the estimation technique. GARCH's distinct phase is relative to ARCH. In GARCH, to determine the parameter estimate, GARCH optimal values should be stated initially

Table 2: Variables used for ARCH models and their correlation.

Parameters	ARCH model	Correlation
High price	1, 1, 0	92.81
Thermal	1, 1, 0	90.19
Precipitation	3, 0, 3	80.21
Jalapeno	23, 0, 13	96.87
Allium sativum	4, 1, 0	84.96
Green hot pepper	2, 1, 0	87.28
Tomato	20, 0, 0	87.72
Okra	21, 1, 0	88.60
Red hot pepper	1, 0, 0	95.20

Table 3: Variables used for GARCH models and their correlation.

Parameters	GARCH model	Correlation
High price	2, 1, 0	91.81
Thermal	1, 2, 0	89.19
Precipitation	3, 0, 1	81.21
Jalapeno	2, 0, 13	82.87
Allium sativum	14, 1, 0	85.96
Green hot pepper	12, 1, 0	86.28
Tomato	20, 10, 0	99.94
Okra	21, 1, 10	87.60
Red hot pepper	1, 0, 0	94.20

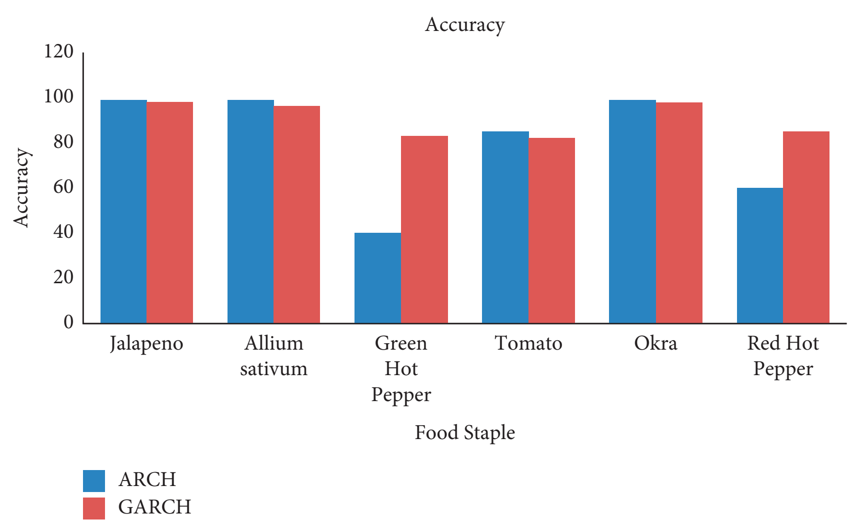

Figure 3: Prediction performance and ARCH-GARCH correlation.

[32]. Then, the outcomes should be used to forecast the demand per response variable.

For each commodity, the projection price outcomes are seen for 3 days straight, and the estimated value is contrasted with the measurement value to see the precision for both models. First, each commodity can describe the right ARCH model [33]. Tables 2 and 3 display the best ARCH and GARCH structures for each parameter used in forecasting. ARCH models are derived from the framework for incorporating stability evaluation, and auto- and partial correlation function tests. Table 2 also indicates the proportion of the strongest ARCH model correlation [34]. As seen in Table 2, the precipitation indicator finds the weakest association as monthly precipitation has strong variability. Table 3 shows the variables used for GARCH models and their correlation.

Figure 3 demonstrates the consistency relation with each asset using ARCH and GARCH. From findings, it can be shown that uncertainties in information motions can trigger poor prediction performance. Multiple variables are another source and their variability is affected by each product price too [35].

Interestingly, as seen in Figure 3, ARCH and GARCH are in strong correlation. The difference in each precision is seen as slight, particularly in standard food products, jalapeno, red cayenne pepper, and tomato. Meanwhile, for red hot pepper and *Allium sativum* staple food products, the accuracy did not much deviate.

The performance of each foodstuff product utilizing ARCH is greater than 80%. Similarly there is 99.84% in jalapeno, 99.60% in okra, 99.52% in tomato, and 90.72% in red hot pepper. Meanwhile, utilizing the GARCH method, we can estimate all foodstuff products with even greater than 80% precision. The precision when using GARCH for each basic product content is as follows: jalapeno 90.94%; okra: 86.73%; tomato: 96.57%; red hot pepper: 85.43%; *Allium sativum*: 93.20%; green hot pepper: 85.43%.

Proportionally, the ARCH has strong performance for essential goods, jalapeno, okra, red hot pepper, and tomato, relative to that of GARCH for two goods, green hot pepper and *Allium sativum*, in this study. This difference is due to the fact that GARCH can deliver decent performance in high uncertainty results. In other terms, if data vary further, GARCH leads to increased precision. A further explanation is that GARCH uses the learning method by estimating each moment regularly. Furthermore, the study estimates the impact of data and information trends in the GARCH method to generate a constant time-based short-term prediction. In other terms, GARCH tends for information fluctuation and reduces the precision of prediction performance.

5. Conclusion

In this research work, multivariable foodstuff pricing was estimated by using ARCH and GARCH models. Both ARCH and GARCH models' findings are seen to be pleasing in achieving high precision. In this study, several aspects can also be enhanced. For potential work, some items can be added like researching staple food prices using variants of GARCH like GARCH-M and EGARCH.

Data Availability

The data used to support the findings of this study are included within the article. Should further data or information be required, they are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

The authors thank Vignan's Lara Institute of Technology & Science, Vadlamudi, for providing characterization support to complete this research work.

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