

Research Article

Wheat Futures Prices Prediction in China: A Hybrid Approach

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Stocks markets play their financial roles of price shocks and hedging just when they are proficient. The imperative highlights of productive market are that one cannot make extraordinary profit from the stocks markets. This research investigates whether China wheat futures price can be predicted by employing artificial intelligence neural network. This would add to our knowledge whether wheat futures market is resourceful and would enable traders, sellers, and investors to improve cost-effective trading strategy. We utilize the traditional financial model to forecast the wheat futures price and acquire out of sample point estimates. We additionally assess the robustness of our outcomes by applying several alternative forecasting techniques such as artificial intelligence with one hidden layer and autoregressive integrated moving average (ARIMA) model. Furthermore, the statistical significance of our point estimation was further tested through the Mariano and Diebold test. Considering random walk forecast as the bench mark, we used a number of economic indicators, trader's expectation towards futures prices, and lagged value of futures price of wheat in order to forecast the evaluation of wheat futures price. The computable significance of out of sample estimations recommends that our ANN with one hidden layer has the best anticipating presentation among all the models considered in this exploration and has the estimating power in foreseeing wheat futures returns. Furthermore, this investigation discovers that the futures price of wheat can be predicted, and the wheat futures market of China is not productive.

1. Introduction

Commodity futures have pulled in a lot of consideration as of late in light of the fact that they encourage value revelation and permit supporting next to alter in product spot costs. By description, futures markets play out the monetary job just when they are productive. One of the main highlights of proficient business sectors is as follows: it is difficult to create irregular benefits from prospects markets. By suggestion, if there is proof that operators are not manufacturing anomalous benefits in prospects markets, then that strengthens one's claim that the futures markets are performing their economic function efficiently!

Value gauges are utilized by both government organizations just as private operators in spite of the fact that not exactly in a similar way. Government organizations give the

value estimates to ranchers to empower them to prepare while this empowers ranchers to boost their income, neither the ranchers nor the administration offices work in the futures market advertises generally. Interestingly, private operators utilize the value conjectures revenue driven creation, by straightforwardly partaking in the futures market markets where these value estimates are resolved. Subsequently, working as theorists, hedgers, merchants, and trade sellers, these private specialists endeavor to drain the futures market for benefit. Obviously, on the off chance that irregular benefits are to be made as venders, at that point everybody will need to sell, and in the event that unusual benefits are to be made as purchasers, at that point everybody will need to purchase, and the market will stop to exist. All things considered, the market would not have the option to serve its prime capacity of value revelation [1, 2].

In this way, prospects markets must be educational effective for their reality. The authors in [3, 4] revealed the three types of market effectiveness: weak type of productivity, semisolid type of proficiency, and solid type of proficiency. Three classes of effectiveness are clarified with regard to data replicated by the market. Below feeble proficiency, the data set is basically verifiable costs. Resource costs uncover all previous data; therefore, it is difficult to make abundance benefit by utilizing venture strategies dependent on authentic information. Semisolid productivity involves that all previous data in addition to all open data that are reflected in costs effectively, for example, organizations' declarations or yearly income figures. In this manner, one cannot acquire abundance benefit dependent on that data. At last, the solid structure productivity requires all data remembering private data to be joined for costs, inferring that even enemy of serious conduct (for example, insider exchanging) would not prompt anomalous benefits. The authors in [5, 6] and [7] showed that the futures markets mirror the semisolid type of effectiveness. A market member exchanges the prospects markets based on precedent costs just as on factors influencing the futures market cost.

Operators in futures markets might be classified into two sorts dependent on their perspectives: the crucial view holders and the specialized view holders [8]. The individuals who settle on their choices dependent on request and flexibility of the ware being referred to are said to hold the major view. They evaluate the natural estimation of the product and the likelihood of related value developments by seeing homegrown interest and flexibility, climate, government strategy, political strength, and different components like worldwide interest and gracefulness too. One would anticipate just profoundly gifted experts with numerous long periods of market insight to be the key view holders. Proof shows that they for the most part follow just a few agreements all at once and study them in incredible detail. Then again, the individuals who settle on their choices based on their value figures utilizing past costs are supposed to be specialized view holders. Intermediaries, factory proprietors, brokers, examiners, and average citizens are specialized view holders.

The two methodologies can be risky. While the previous way to deal with gauging is exceptionally escalated in data and information, the last considers market developments to be irregular, making it incredibly hard to anticipate the market [8]. At times, it happens that the forecast of the specialized school is exact, and huge quantities of individuals start to embrace a particular situation on the lookout because of which the market overshoots its characteristic worth. This empowers operators of the previous sort to utilize their insight into the market to procure strange benefit.

Evidence shows that most of the market members, viz., traders, formers, philosophers, specialists, and speculators, by and large presentation prospects market conduct that fall under the specialized methodology, and this is the reason we are keen on considering whether the futures market cost of wheat can be precisely figured. Further, note that we do not

have to investigate the estimation of the wheat spot cost since it has just settled that the prospects cost is a decent forecaster of the spot value [9].

There are enormous quantities of studies that have analyzed whether the costs of ware, stock records, loan fees, and money prospects can be anticipated. The previous examinations have assessed their outcomes utilizing either the econometric method or a productive exchanging monetary measurement (financial procedures that need prior information are different in structure). The writing with respect to the consistency of prospects returns is blended. A few investigations have discovered that the prospects returns cannot be anticipated, while others have discovered that the futures market returns can be estimated.

In financial market writing, the subject of the consistency of futures market costs fundamentally has been widely examined. In any case, there are not many examinations concerning rural product markets. Among these couple of studies, the authors in [10] analyzed the consistency of agricultural product and money futures market and found that farming, metal, and cash prospects returns can be all around anticipated utilizing instrumental factors, for example, depository charge yields, value profit yields, and so on. The author in [11] looked at consistency of ware and monetary futures market returns utilizing instrumental factors. He found that instrumental factors help in anticipating metal, stock file, and financing cost futures, yet these instruments neglect to gauge the farming and cash futures.

Furthermore, there are likewise blended observational confirmations with respect to estimation of prospects costs utilizing a financial metric structure. The authors in [12] credited the wellspring of benefits in cash prospects to failure of the market. On the opposite, the authors in [13–15] and [16] found that the market members' benefit from exchanging futures market contract was not anomalous, and the authors in [17] credited the wellspring of benefit to atmosphere instead of the capacity of the market member to foresee the market better and reasoned that the ware and budgetary prospects markets were effective [18, 19].

In China, the legislature has been advancing agrarian futures market since the commencement of China's rustic changes in 1978 known as horticulture changes. With agribusiness being one of the main area in the China economy, this examination explores whether futures market costs can be figured in the China wheat market, with the end goal of finding whether the wheat futures market in China is proficient [16, 20, 21]. By suggestion, this would address the issue of whether representatives, dealers, and examiners in the China wheat market can build up a beneficial exchanging technique [16] and whether that would help in supporting against changes in spot costs [8, 22].

The authors in [23] developed a novel model selection framework based on time series features and forecast horizons. A number of features were used to illustrate agricultural commodity prices, and three hybrid models were identified as the best forecast models, namely, support vector regression (SVR), artificial neural network (ANN), and extreme learning machine (ELM). Furthermore, the authors in [23] applied random forest (RF) and support vector

machine (SVM) to study the primary relationships between the features and the performances of the candidate models. In these investigations, various examinations have analyzed the consistency of the rural items prospects costs fundamentally, and every one of these investigations has focused on the US and hardly any other futures markets. None of the examinations has analyzed the consistency of China futures price up until now.

Given the above foundation, it is clear that the essential climaxes of China farming futures markets are not quite the same as the futures market of advanced countries. Along these lines, this examination fills the exploration hole by utilizing the day by day information of wheat prospects from June 15, 2010, to October 20, 2020.

The main contribution of this research is as follows. We utilize the conventional model to forecast the advancement of wheat futures price and utilize out of sample point estimation. We at that point test the factual noteworthiness of the point estimation utilizing the Diebold and Mariano test. Besides, we evaluate the robustness of our outcomes by utilizing a few elective models, viz., ARIMA measure, neural network strategies, and so on. We think about random walk (RW) estimation as the benchmark since it is a straightforward estimate. The examination finds that the three-layer artificial neural network model bypasses all the four models, suggesting that the futures market price of wheat can be projected utilizing cross breed strategies.

The remaining of this research is organized as follows. Section 2 explains conventional econometric models considered in this research in detail. Section 3 presents hybrid modeling procedure, data used in this research, and computational environment. Section 4 presents application of the models on most recent data set with explanation. Finally, Section 5 concludes this research with polices implication and future research.

2. Econometrics Forecasting Models

2.1. Conventional Model. An ordinary model guesses that futures price is controlled by the previous qualities, dealers' assumptions regarding their future qualities, and other significant financial elements [24]. According to the theory utilizing the Bayesian data rules to pick the ideal slack duration, this is indicated the accompanying assessment model:

$$\Delta \ln FP_{wt} = \beta_0 + \beta_1 \Delta \ln FP_{w(t-1)} + \beta_2 \Delta \ln FP_{r(t-1)} + \beta_3 \Delta \ln FR_{R-W(t-1)} + \beta_4 \text{Basis}_{t-1} + \beta_5 R_{t-1} + \beta_6 \Delta j_{t-1} + \varepsilon_t, \quad (1)$$

where Δ indicates the 1st dissimilarity, \ln is the natural logarithm, FP_w is the prospect value of wheat, FP_r is the prospect value of rice, j is the valid interest rate, $Basis$ is the distinction among the mark and prospect value of wheat, FP_{R-w} is the Russia prospect value of wheat, and R is the ratio of high cost to little cost of wheat potential. Fraction of big price to small value determines the tendency of the promotion. Consequently, ratio of big to small price of wheat is utilized as replacement of merchants' prospect. Detailed

description of variables is presented in Table 1 whereas summary statistics and relevant test statistics are shown in Table 2 in Section 3.

If the ratio is high, then the promotion is in ascending movement. It involves that more and more fresh market applicants will come into the market. If ratio is small, afterward the market is in descending movement and involves that the offered market contributors will advertise their agreements.

2.2. Autoregressive Integrated Moving Average Model. We utilize univariate autoregressive integrated moving average (ARIMA) models to inspect the amount to which the precedent costs of prospects values of wheat can be utilized to anticipate the wheat prospect value. For the confirmed point, we create the data motionless with the assistance of distinction. We first fit the best model based on the past data and then make the forecast. Our two best fitted models on the time series data of prospect values of wheat are ARMA (1, 1, 1) and ARMA (1, 1, 2). We estimate the subsequent ARMA (1, 1, 1) model:

$$\Delta \ln y_t = \beta_0 + \beta_1 \Delta \ln y_{t-1} + \vartheta_1 \varepsilon_{t-1} + \varepsilon_t. \quad (2)$$

Those history standards of futures prices of wheat influence optimistically the present futures price of wheat. Likewise, if β_1 is negative and important, it represents the previous prices of prospective profit of wheat impact negatively. The moving average coefficient is represented by ϑ_1 . The positive and significant value of ϑ_1 presents that the previous values of wheat impact positively on the current value of wheat as compared with those of the future. In estimation, we represent the following ARMA (1, 1, 2) model:

$$\Delta \ln y_t = \beta_0 + \beta_1 \Delta \ln y_{t-1} + \vartheta_2 \varepsilon_{t-2} + \vartheta_1 \varepsilon_{t-1} + \varepsilon_t. \quad (3)$$

The moving average coefficient of order two is ϑ_2 . When the value of ϑ_2 is positive and significant, it shows that the current value of wheat future values is affected positively by the past error (shocks) two days ago.

3. Hybrid Model

3.1. Hybrid Artificial Neural Network (ANN). We utilize the neural network procedure to evaluate the strength and accuracy of the prediction. A neural network technique is information driven anticipating strategy that endeavors to catch the basic densities whereas assessing the correlation of premium. It is a progress over the conventional degeneration structure in which it depends on fewer prohibitive presumptions and exertions with new adaptable practical structures. The useful structure requires not be direct in a neural organization. It is a nonlinear semiparametric model [24, 28]. It links the data information to the resultant layer by means of an arrangement of transitional connections alluded to as neurons, wherein neurons cooperate with one another. This approach has been generally utilized in the machine learning [5, 24, 29]. The clarification of the designed artificial neural network (ANN) is as per the following.

TABLE 1: Explanation of variables with expected sign and sources.

Variables	Definition	Exp. sign	Source
FP_{Russia_w}	Russian wheat futures prices	+	[25]
FP_w	Wheat futures prices	-	[16]
FP_r	Rice futures price	±	[26]
J	Real rate of interest	-	[6]
Basis	Distinction among the mark and prospect costs of wheat	-	[6]
R	Wheat future price ratio (high to low)	+	[27]

TABLE 2: Descriptive statistics.

	Wheat FP	Rice FP	Real interest rate	Russia wheat FP	Origin	High to low price ratio
Panel A: wheat prospects prices and economic variables summary statistics						
JB-statistic	139.326***	51.998***	114.145***	58.149***	289.486***	1247.737***
ADF	-2.285	-1.469	-2.325	-2.407	-4.715***	-7.430***
DF-GLS	-2.288	-1.326	-1.098	-2.248	-3.726***	-7.275***
Mean	3.128	3.476	-0.488	11.709	0.015	1.009
Min.	3.033	3.310	-8.080	11.210	-0.089	1.000
Max.	3.225	3.702	6.410	12.160	0.186	1.043
Std. dev	0.055	0.093	2.997	0.227	0.041	0.006
Kurtosis	—	—	2.387	2.390	4.419	7.545
Skewness	0.230	0.368	-0.549	-0.412	1.201	1.796
Panel B: economic variables (first difference) and wheat prospective prices statistics summary						
JB-statistic	531.033***	0.738	36977.900***	267.674***	—	—
ADF	-48.144***	-45.984***	-36.392***	-47.781***	—	—
DF-GLS	-14.502***	-45.826	-4.146**	-13.644***	—	—
Mean	0.046	0.005	0.085	-0.001	—	—
Min.	-5.316	-3.989	4.030	0.091	—	—
Max.	4.166	3.989	-3.300	-0.096	—	—
Std. dev	0.741	2.011	0.445	0.023	—	—
Kurtosis	5.371	2.985	3.069	0.135	—	—
Skewness	0.081	0.041	30.246	5.108	—	—
Observations	951	951	951	951	951	951

Note. FP means futures price; JB-statistic means Jarque–Bera test; ADF means Augmented Dickey Fuller; DF-GLS means Dickey Fuller generalized least square *, **, and *** represent significance level at 10%, 5%, and 1% implying that the null hypothesis is rejected. Null hypothesis for Jarque–Bera test is that the data are normally distributed; null hypothesis for ADF and DF-GLS is that the series has a unit root.

3.1.1. *Three-Layer Artificial Neural Network.* The anticipated neural network includes 3 layers such as the input, the intermediate middle, and the resulting layers whereas the input layer closely resembles the independent variables in the conventional regression model and the resulting layer relates to the dependent variable. The intermediate layer is the distinguishing component of a neural network over traditional regression. This hidden layer tends to get denser and, indeed, multi-layered as the phenomenon of interest gets more complicated.

An ANN comprises of preparing components; we call it neurons. Every neuron resembles a variable. As shown in Figure 1, the arrows connecting the neurons imply the boundaries of neurons. The boundaries of the neurons are the loads related with them. In this strategy, we interface the contribution to the resulting information by means of an arrangement of neurons, and these neurons gain from different neurons.

The steps involved in the development of our proposed artificial neural network for wheat futures value prediction are as follows:

Step 1. Design the structure of the network (i.e., numeral of effort nodes, figure of joint and coatings that are hidden, transmit purpose, and productivity joint) in the case of ANN effort nodes are descriptive variables.

Step 2. Partition the data into two groups (i.e., training and testing). The first 850 observations of data set are used for tuning purpose and the residual 101 model positions to authorize the model.

Step 3. Rescale explanatory and output variables in the interval of 0 to 1 using the following formula: observed-minimum/range.

Step 4. Set the starting instruction burden and initiate an exercise period.

Step 5. Present the level efforts at neurons 0, 1, 2, 3, 4, and 5 using standard approach outlined by [27] with the help of RATS software.

Step 6. Each neuron in the key coating accepts its balanced price and conveys it to every neuron in the secreted coating. There is similar dispensation of contribution at other two buried neurons. We have one secreted neuron.

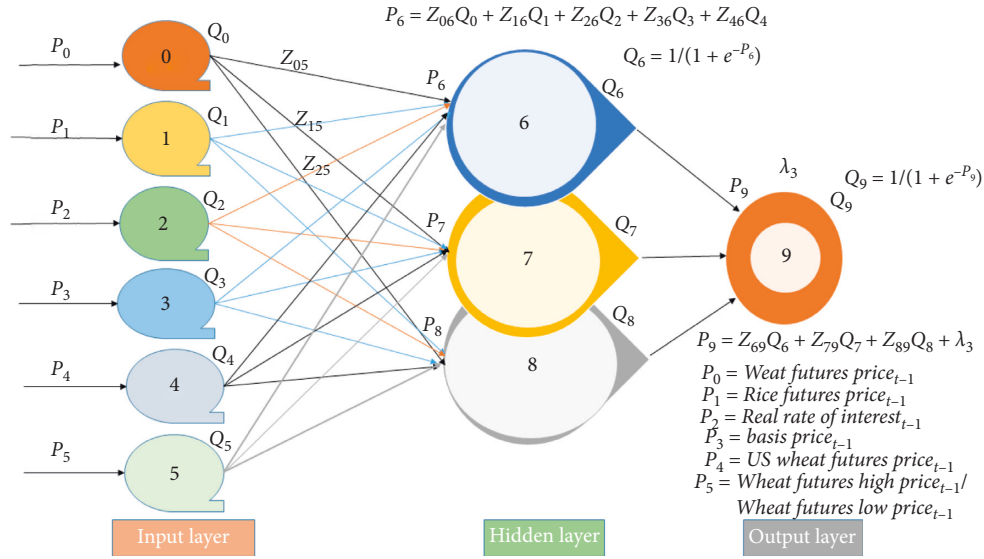


FIGURE 1: Three-layer artificial neural network.

Step 7. Assign weights and figure the inputs to getting nodes, i.e., $P_6 = W_{06}Q_0 + W_{16}Q_1 + W_{26}Q_2 + W_{36}Q_3 + W_{46}Q_4 + W_{56}Q_5$. These weights are recall and aptitude of the system.

Step 8. Renovate the subjective contribution at every unseen node to production in interval 0 to 1. We utilized the logistic function to express the association between input and output of neuron.

Step 9. Put in secreted neuron productivity as input to output node.

Step 10. Transform weighted inputs P_9 to output of Q_9 in the interval 0 to 1 with the application of logistic function. Output of neuron 9 can be determined as follows:

$$Q_9 = \frac{1}{1 + e^{-P_9}}, \quad (4)$$

Step 11. Calculate errors in the output, i.e., $e_i = P_9 - Q_9$.

Step 12. In the training data set, tune weights set so as to attain the smallest quantity outstanding average standard error (MRMS) value.

Step 13. Repeat steps 5–12.

Step 14. Compute epoch RMS value (repeat steps 5–14 until low value of MRMS is not obtained).

Step 15. Validate ANN results on testing data set.

Step 16. Use the ANN model for forecasting.

3.2. *Data and Computational Environment.* Data used in this research are taken from different sources for a sample period of June 15, 2010, to October 20, 2020 (daily data which are available six days per week). The associated financial indicators that are under consideration in this investigation are as follows: the actual rate of interest, the

futures price of rice, futures price of wheat in Russia, and the premise (characterized as the contrast among futures market and spot costs). Data on trader’s expectations are not accessible; subsequently, the proportion of low and high cost is the intermediary of merchant’s assumption regarding wheat futures price. The information on futures price of rice and wheat are acquired from China Financial Futures Exchange (CFFEX), rate of interest from Bank of China site, wholesales value index from Public Agency of Insights of China, the future price of wheat in Russia from Exchanging Financial Matters Information, and buyer value list of Russia from Central Bank Monetary Information (FRED)⁵. Various futures contracts are exchanged simultaneously consistently. Thus, we have taken the close by contract information for our investigation in light of the fact that the close by contract is the most fluid agreement. Yet, the close by prospects contract should be at any rate one month away [30].

All outcomes revealed in this article are done in R-studio computational environment. The traditional ARIMA (p, d, q) was fitted on the data set using the “forecast” package in R language whereas for the ANN model we take help from “caret” package with “mlp” function in R.

4. Application of Artificial Neural Network to Real-Life Data Set

To analyze the wheat futures price pattern statistically, we start by eliminating trend, the effect of inflation, and seasonality of the prospects costs of wheat and other logical factors, viz., futures cost of rice and Russia wheat futures cost. We utilized dummy variables to check the presence of the seasonal impact. Nevertheless, there is no evidence of seasonal effect in the futures price for wheat and rice.

Next, we estimated the conventional model, in which we assume futures prices of wheat as function of its own past value and lagged economic factors [24]. Through ordinary least square technique, we estimate our model. Table 3 presents the

TABLE 3: Conventional model variables and coefficient estimation.

Variables	Coefficient
Constant	-8.209* (4.284)
$FP_{w(t-1)}$	0.045 (0.037)
$FP_{r(t-1)}$	-0.033 (0.022)
$FP_{R-W(t-1)}$	3.182** (1.236)
$Basis_{t-1}$	-0.329 (0.547)
R_{t-1}	8.196* (4.206)
R^2	0.015
\hat{j}_{t-1}	-0.096 (0.079)
Observations	951

Note. *, **, and *** specify statistical significance at the 10%, 5%, and 1% levels, respectively, value in parentheses represent corresponding standard errors, and test statistics: $F(6, 942) = 3.289$ (P value 0.031).

effects of the traditional variable model for wheat futures returns for the sample time frame May 21, 2009, to October 20, 2020. We account the expected coefficients, standard errors, R^2 , and F-statistic rate for wheat prospect returns. *, **, and *** point out numerical importance of the expected limitations at the 10%, 5%, and 1% levels, correspondingly.

The value of R^2 is observed as 0.15%, and it acquired higher in several prospective markets values as described by [6, 11, 31, 32].

Our results indicate that Russian wheat production and high to low cost proportion have positive and serious effects on the future returns of wheat in China. The futures return of wheat in Russia coefficient is 3.182 which is critical at 5 percent degree of significance. It recommends that if the profits on prospects agreement of wheat in Russia increments by 1 percent, at that point the profits on futures agreement of wheat in China increments by about 3.1 percent. This is because of the wide-running monetary changes that have occurred in China succeeding to the financial emergency of 1978, bringing about expanding advancement and globalization of business sectors and evacuation of state controls. These financial changes have prompted the mix of China economy with the worldwide market. The ratio of wheat high to low price value coefficient is 8.196 that is huge at 10% level of noteworthiness. It recommends that in the event that the proportion of high-low cost increments by one, at that point the profits on prospects agreement of wheat in China increments by 8.2%. We have utilized proportion of high-low cost as proxy for traders' assumptions regarding the prospects costs. The estimation of the proportion of high-low price proposes that the market is in rising pattern. Although, we observe that futures price of rice is not significant in the model. We follow the procedure of the Box-Jenkins modelling approach to estimate the futures returns of wheat for the sample period June 2010 to May 2020. The two best fitted models based on AIC value are the ARMA (1, 1, 1) and ARMA (1, 1, 2). Table 4 presents the results of all fitted ARIMA models for wheat price data set, respectively.

In the next step, we evaluate the sample forecast of wheat futures price and the out of sample forecast performances. Then, we evaluated and compared the out of sample forecast performance from the random walk, ARMA (1, 1, 1), ARMA (1, 1, 2), artificial neural network, and conventional model.

TABLE 4: All possible fitted models along with log-likelihood and AIC.

Model	Log-likelihood	AIC
ARIMA (1, 1, 1)	-179.99	355.49
ARIMA (2, 0, 2)	-180.52	369.03
ARIMA (1, 0, 2)	-175.62	361.24
ARIMA (1, 1, 2)	-178.74	355.48
ARIMA (2, 1, 2)	-172.1	354.19
ARMA (2, 0, 1)	-172.21	354.43

4.1. Forecasting. We have fitted all the models under consideration for the period June 2010 to May 2020 and produced the out of sample forecasts. We have employed Theil's U-statistic to measure the forecast correctness. Theil's U-statistic for random walk, conventional model, ARMA (1, 1, 1), ARMA (1, 1, 2), and the triple layer artificial neural methods are 1.052, 1.035, 1.045, and 1.031, respectively, as shown in Table 5. Theil's U-statistics more than 1 for four models, that is, applying the naïve forecast as compared with the model forecasts are much better [33]. As compared with others, Theil's U-statistic is inclined by the mean squared error of the naïve forecast. As a result, to ensure forecast correctness, RMSE and MAE are used as it has been used by [33]. This model with the smallest value of RMSE and MAE provides the most accurate forecast. The values of RMSE and MAE for the random walk, conventional model, ARMA (1, 1, 1), ARMA (1, 1, 2), and artificial neural network values are shown in Table 5.

First, we find that the estimated value of RMSE (root mean square error) for the conventional model, ARMA (1,1,1), ARMA (1,1,2), neural network, and random walk are 0.7301, 0.7975, 0.6986, 0.6937, and 0.7487, respectively. The artificial neural network has the smallest value of RMSE. We consider the MAE, and the expected value of RMSE for the predictable model, ARMA (1, 1, 1), ARMA (1, 1, 2), neural network, and random walk is 0.5728, 0.5873, 0.5878, 0.5728, and 0.5799, respectively. The ANN has the minimum value of MAE. On the basis of RMSE and MAE, the ANN model provides the majority accurate forecast of the wheat futures earnings. Next, we have employed the Diebold-Mariano (DM) analysis to observe whereas the RMSE and MAE from the model under consideration are statistically significant from the benchmark model (random walk). The Diebold-Mariano (DM) analysis out of sample forecast of model measurement is shown in Table 6.

The valid assumption analysis tests that the conventional model and random walk model execute similar pattern. Thinking about the RMSE 1st, the DM analysis recommends that the invalid speculation is dismissed for conventional model, ARMA (1, 1, 2) with yet not for neural networking. It suggests that the ANN model is a superior indicator than for conventional model, ARMA (1, 1, 2), and random walk model. This finding is contradicted with the investigation done by [34, 35] for India while steady with an examination direct by [16] utilizing the APSSO-SVR method. However, there is no distinction in determining exactness between the ARMA (1, 1, 1) and the random walk model. With respect to the MAE, the DM test results recommend that the invalid

TABLE 5: Performance evaluation matrix of the models under consideration for wheat futures price series.

	Random walk	Conventional model	ARMA (1, 1, 1)	ARMA (1, 1, 2)	Three-layer ANN
MAE	0.5799	0.5866	0.5873	0.5878	0.5728
RMSE	0.7487	0.7301	0.7975	0.6986	0.6937
Theil's U	—	1.052	1.035	1.045	1.031

Note. MAE: mean absolute error; RMSE: root mean square error.

TABLE 6: The Diebold–Mariano future prediction accuracy test.

	Artificial neural network	ARIMA (1, 1, 1)	ARIMA (1, 1, 2)	RW	Conventional model
MAE	0.4163*	0.4975	0.4986*	0.4948	0.4301*
RMSE	0.7999***	0.7673*	0.7678*	0.7627	0.7766**

Note. *, **, and *** specify statistical significance at the 10%, 5%, and 1% levels, respectively.

speculation is dismissed for variable model, ARMA (1, 1, 1), and ARMA (1, 2). It infers that the ANN model is a superior indicator than for traditional model, ARMA (1, 1, 1), ARMA (1, 1, 2), and random walk on account of China. In this way, we infer that the ANN has the best determining presentation, and ANN beats all the four models considered. This infers that the prospects cost of wheat can be effectively anticipated utilizing progressed cross breed strategies, and wheat futures market is not proficient in China which has solid help from writing.

5. Conclusion and Implementation

Utilizing daily data of wheat price in this research, researchers for the first time proposed whether China wheat futures price can be predicted. By utilization of few elective model determinations, viz., ARMA (1, 1, 1), ARMA (1, 1, 2), the random walk, traditional variable model, and neural network technique, we develop the point estimates and assess their factual importance operating by means of Diebold–Mariano analysis. We have utilized the recursive forecasting technique to obtain the remaining out of sample point forecasts.

The quantifiable significance of out of sample estimations recommends that ANN has the best anticipating presentation among all the models considered in this exploration and has the estimating power in foreseeing wheat futures returns. Subsequently, the theory that the wheat futures market is instructively productive can be dismissed. Our outcomes show that China wheat future price in principle can be estimated. Regardless, it has been set up that the wheat item futures market is not proficient, which disgraces exchanging of wheat futures on public trades.

This is due to the reason that commodity such as wheat futures can be utilized to fence against change in commodity spot costs. Risk management plays important role in futures market [16, 36, 37]. Furthermore, essential view holders who settle on their choices dependent on request and gracefully of the hidden product will exchange the wheat futures market to acquire benefits from the market.

The exploration of this work leads us to the conclusion that the Chinese experts need to initiate awareness about importance of wheat development and start meaningful program among the farmers (and other stockholders) about the advantages of value disclosure and risk management. This will expand the volume of prospects agreements and make the futures advertises more proficient.

5.1. Future Research Work. There are several directions for future research; we are going to highlight some of them here. First, there is a need to explore the US and Russian (the world top exporter of wheat) wheat futures market with the newly developed advance techniques such as ANN and compare the results with one obtained for China. Second, as risk management through hedging is an essential function of futures market, therefore, it is necessary to developed intelligence-based strategies that help investor in making their decisions centered on demand and supply of the underlying commodity and will trade in the wheat futures market to earn profits from the market. These are some points one may consider for future research.

Abbreviations

- CFFEX: China financial futures exchange
- RMSE: Root mean square error
- ARIMA: Autoregressive integrated moving average
- ANN: Artificial neural network
- BOC: Bank of China
- DM: Diebold–Mariano
- JB: Jarque–Bera test
- MRMS: Minimum residual mean standard error
- AIC: Akaike information criteria.

Data Availability

The information on prospects cost of rice and reason for wheat are acquired from China Monetary Fates Trade (CFFEX) [38], pace of revenue from Bank of China site, discount value records from Public Agency of Insights of China, the fates cost of wheat in Russia from Exchanging Financial matters information and buyer value list of Russia

from Central bank monetary information (FRED) available at [39] (<https://tradingeconomics.com/>) and [40] (<https://fred.stlouisfed.org/>).

Ethical Approval

This article does not contain any studies with human participants performed by any of the authors.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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