Predicting Wheat Futures Prices in India

Abstract

This paper addresses the question of whether Indian wheat futures prices can be forecast. This would add to our knowledge whether wheat futures market is efficient, and would enable brokers, traders and speculators to develop profitable trading strategy, and would help in hedging against the changes in spot prices. We employ the economic variable model to predict the evolution of wheat futures prices, and employ point out of sample forecasts. We also evaluate the robustness of our results by employing several alternative specifications, viz. ARMA process and artificial neural network technique. The study finds that the random walk model outperforms all the four models, implying that the futures price of wheat cannot be forecast.

Keywords: Futures market, forecasting, artificial neural network (ANN) and agricultural finance

JEL Classification: G13, C53, C45 and Q14

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"*Derivatives are an extremely efficient tool for risk management*"
"Derivatives are financial weapons of mass destruction"
–Warren Buffett

1. Introduction

Commodity futures have attracted a significant amount of attention in recent years, because they facilitate price discovery and allow hedging against changes in commodity spot prices. By definition, futures markets perform their economic[1] role only when they are efficient.[2] One of the most important features of efficient markets is that it is impossible to make abnormal profits from futures markets. By implication, if there is evidence that agents are not making abnormal profits in futures markets, then that strengthens one's claim that the futures markets are performing their economic function effectively![3]

In India, the government has been promoting agricultural futures markets since the initiation of economic reforms in 1991 (Government of India 2000, 2001, 2008). Previous studies show that Indian agricultural commodity futures markets perform the economic roles of price discovery and hedging (Kumar and Pandey 2011; Sehgal et al. 2014; Kumar 2017) efficiently. Agriculture being a key sector in the Indian economy, this paper investigates whether futures prices can be forecast in the Indian wheat market, with a view to discovering whether the wheat futures market in India is efficient (Hartzmark 1991; Miffre 2001b; Kostantinidi and Skiadopoulos 2011). By implication, this would address the issue of whether brokers, traders and speculators in the Indian wheat market can develop a profitable trading

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[1] The economic functions of futures markets are price discovery and hedging. Price discovery is the ability of the market to discover true equilibrium prices in the economy. Hedging refers to the minimization of price risk by taking the appropriate position in futures markets.

[2] The following are the features of efficient market: firstly, one cannot earn money without taking risk. Secondly, market revealing all available information. Thirdly, movement of the market is random, Lastly, it is impossible to make abnormal profits from the markets based on the information at time t. (Malkiel and Fama 1970; Jensen 1978).

[3] The futures price of a commodity reflects the relative demand and supply of that commodity both in the present and the future (Edward and Ma 2003). If futures markets can be forecast, everyone will become either a seller or a buyer, depending on the forecast; but in that case, the market will cease to exist.

strategy (Grudnitski and Osburn 1993), and whether that would help in hedging against changes in spot prices (Edward and Ma 1992, Carter 2003).

Price forecasts are used by both government agencies as well as private agents, although not quite in the same manner. Government agencies pass on the price forecasts to farmers, to enable them to plan ahead. While this enables farmers to maximize their revenue, neither the farmers nor the government agencies operate in the futures markets for the most part. In contrast, private agents use the price forecasts for profit-making, by directly participating in the futures markets where these price forecasts are determined. Thus, operating as speculators, hedgers, traders and swap dealers, these private agents attempt to milk the futures market for profit. Of course, if abnormal profits are to be made as sellers then everyone will want to sell, and if abnormal profits are to be made as buyers then everyone will want to buy, and the market will cease to exist. In that case, the market would not be able to serve its prime function of price discovery (Schwarz and Szakmary 1994). So, futures markets have to be informationally efficient for their existence.

There are three forms of market efficiency: weak form of efficiency, semi-strong form of efficiency, and strong form of efficiency (Malkiel and Fama 1970). The above three categories of efficiencies are explained in the context of information reflected by the market. Under weak efficiency, the information set is simply historical prices. Asset prices reveal all past information; as a result, it is impossible to make excess profit by using investment tactics based on historical data. Semi-strong efficiency entails that all past information plus all public information is reflected in prices already, such as companies' announcements or annual earnings figures. Therefore, one cannot earn excess profit based on that information. Finally, the strong-form efficiency requires all information including private information to be incorporated in prices, implying that even anti-competitive behaviour (such as insider trading, for instance) would not lead to abnormal profits. The futures markets reflect the semi-strong form of efficiency (Konstantinidi and Skiadopoulos 2011). A market participant trades in the futures markets on the basis of past prices as well as on factors affecting the futures price.

Agents in futures markets may be categorized into two types based on their views: the fundamental view-holders and the technical view-holders (Carter 2003; Plummer 2009). Those who make their decisions based on demand and supply of the commodity in question are said to hold the fundamental view. They assess the intrinsic value of the commodity and the probability of associated price movements by looking at domestic demand and supply, weather, government policy, political stability, and other factors like international demand and supply as well. One would expect only highly skilled professionals with many years of market experience to be the fundamental view holders. Evidence shows that they generally follow only two to three contracts at a time, and study them in great detail. On the other hand, those who make their decisions on the basis of their price forecasts using past prices are said to be technical view-holders. Brokers, mill-owners, traders, speculators and common people are technical view-holders.

Both approaches can be problematic. While the former approach to forecasting is highly intensive in information and data, the latter considers market movements to be random, making it extremely difficult to predict the market (Carter 2003). Sometimes it happens that the prediction of the technical school is accurate, and large numbers of people begin to adopt a specific position in the market, as a result of which the market overshoots its intrinsic value. This enables agents of the former type to use their knowledge of the market to earn abnormal profit.

Evidence shows that the majority of the market participants, viz. traders, mill-owners, speculators, brokers and investors, generally display futures market behaviour that falls under the technical approach, and this is why we are interested in studying whether the futures price of wheat can be accurately forecast. Further, note that we do not need to explore the forecasting of the wheat spot price, because it has already established that the futures price is a good forecaster of the spot price (Sehgal et al. 2014; Kumar 2017).

There are large number of studies that have examined whether the prices of commodity, stock indices, interest rates and currency futures can be predicted. The past studies have evaluated their results using either econometric technique or a profitable trading economic metric.[4] The literature regarding the predictability of futures returns is mixed. Some studies have found that the futures returns cannot be predicted, while others have found that the futures returns can be forecasted.

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[4] Statistical technique means that we make a forecast based on the past prices only. However, economic metric technique implies that we require the data for the various type of traders who actually trade in the market. We look at the prices they receive, costs they incur, opportunity cost of investing, then we calculate the overall profit of these investors in the market. If they make abnormal profits, we conclude that markets can be predicted.

In financial market literature the topic of the predictability of futures prices per se has been extensively discussed. However, there are very few studies concerning agricultural commodity markets. Among these few studies, Bassembinder and Chan (1992) examine the predictability of agricultural commodity and currency futures and find that agriculture, metal and currency futures returns can be well-predicted using instrumental variables such as treasury bill yields, equity dividend yields, etc. Miffre (2001b) examines predictability of commodity and financial futures returns using instrumental variables. He finds that instrumental variables help in predicting metal, stock index and interest rate futures, but these instruments fail to forecast the agricultural and currency futures.

In addition, there are also mixed empirical evidences regarding forecasting of futures prices using an economic metric framework. Talyor (1992) and Kearns and Manners (2004) attributed the source of profits in currency futures to inefficiency of the market. On the contrary Kho (1996), Miffre (2002), Wang (2004) and Yoo and Maddala (1991) discovered that the market participants' profit from trading in futures contract were not abnormal, and Hartznark (1991) attributed the source of profit to luck rather than the ability of the market participant to predict the market better, and concluded that the commodity and financial futures markets were efficient (Jensen 1978).

In the existing literature, numerous studies have examined the predictability of the agricultural commodities futures prices per se, and all these studies have focused on the US and few other developed markets. None of the studies has examined the predictability of Indian futures prices so far.

The futures markets in India are different from agricultural futures market of developed economies in the following ways. First, there is evidence on the financialization[5] of agricultural commodity markets of developed countries (Henderson, Pearson and Wang 2014). However, foreign institutional investors (FIIs) are not allowed in Indian agricultural commodity futures markets. Second, the volume of transaction in Indian agricultural futures market is less than the volume of futures transactions in USA, and China and is, therefore, less efficient (Gulati et al. 2017). Third, the futures market is anchored to spot market. The spot market in USA and China is highly developed (Gulati et al. 2017). However, there are several weaknesses in the Indian

[5] Financialization of commodity markets implies that the flows of the financial investors have impact on the agricultural commodity futures prices.

spot markets. There is the problem of warehouses, finance etc. Till these weaknesses are improved, it will be hard for the futures market to grow far ahead of them. Whenever futures markets try to grow faster than spot markets, the gap between the two gets broadened, providing a window of opportunity for speculators to exploit the markets (Government of India 2008). Fourth, unlike USA and China, the government often intervenes in Indian agricultural futures markets (Gulati et al. 2017). Finally, unlike China, there is no compulsory delivery of the agricultural commodities on the expiry of futures contracts. Compulsory delivery[6] of the agricultural commodities on the expiry of futures contracts will help in preventing speculative activities in the market (Gulati et al. 2017).

Given the above background, it is apparent that the basic features of Indian agricultural futures markets are different from the futures markets of developed countries. So, this study fills the research gap by employing the daily data of wheat futures from May 21, 2009 to August 28, 2014. Wheat is the staple food grain crop of India, and a significant commodity beside rice. India is the third largest producer of wheat in the world, and it has the largest area under wheat production in the world.

We make use of the economic variable model to predict the evolution of wheat futures prices, and employ out of sample point forecasts. We then test the statistical significance of the point forecast using Diebold and Mariano test. Furthermore, we evaluate the robustness of our results by employing several alternative specifications, viz. ARMA process and Neural network techniques etc. We consider random walk (RW) forecast as the bench mark because it is a naive forecast. If forecast from other models does better than RW, we say that the wheat futures prices can be forecast, and vice versa. The study finds that the random walk model outperforms all the four models, implying that the futures price of wheat cannot be predicted.

This chapter is organized as follows. Section 4.2 describes the forecasting models used in the present study. Section 4.3 presents a description of the data used. Section 4.4 describes the forecast evaluation criteria. Section 4.5 presents the estimation results concerning the out-of-sample forecast, and evaluation of the forecasts from different models in statistical terms. Finally, Section 4.6 provides the conclusions.

[6] Compulsory delivery based contracts may not be required when the futures markets are fully developed. In USA, there is no compulsory delivery based futures contracts.

4.2. Forecasting Models

4.2.1. A Structural Model

A standard structural model hypothesizes that futures prices are determined by their own past values, traders' expectations about their future values, and other relevant economic factors (Grudnitski and Osburn 1993). Following this hypothesis, and using the Bayesian and Schwartz information criteria to choose the optimum lag length, we specify the following estimation model:

$$dlnFP_{wt} = \alpha_0 + \alpha_1 dlnFP_{w(t-1)} + \alpha_2\, dlnFP_{g(t-1)} + \alpha_3\, di_{t-1} + \alpha_4\, BASIS_{t-1} + \alpha_5 dlnFP_{w\_US(t-1)} + \alpha_6 R_{t-1} + \epsilon_t \quad (1)$$

where d denotes the first difference, ln is the natural logarithm, FP_w is the futures price of wheat, FP_g is the futures price of gram, i is the real[7] interest (call money) rate, $BASIS$ is the difference between the spot and futures prices of wheat, FP_{w_US} is the US futures price of wheat, and R is the ratio of high price to low price of wheat futures. We have taken the ratio of high price to low price of wheat to proxy for traders' expectation. Ratio of high price to low price measures the trend of the market. If the ratio is high, then the market is in upward trend. It implies that more and more new market participants will enter the market. If ratio is low, then the market is in downward trend implying that the existing market participants will sell their contracts.

The factors that we consider as regressors are those that are likely to have predictive power in futures and equity markets (Kostantinidi and Skiadopoulos 2011, Welch and Goyal 2008). In the Indian context, the price of gram likely influences the price of wheat, because gram and wheat have a substitutability relationship in production and a complementarity relationship in consumption. A second important factor is the real rate of interest, which has an inverse relationship with commodity futures price. Thus, a lower interest rate lowers the cost of holding inventory, thereby raising inventory demand, lowering commodity market supply, and raising the market price of the commodity. We proxy this factor by the interest

[7] Real rate of interest is the nominal interest (call money) rate minus inflation. Monthly data for whole sale price index is available, so we have calculated inflation for the month and used it for all days in that particular month.

rate in the call money market. Third, another economic factor is the basis. Basis[8] can be decomposed into the risk premium and difference between the expected spot price and current spot price. Therefore, basis have the power to predict the futures risk premium (Fama and French 1987). Furthermore, we have taken the ratio of high price to low price of wheat to proxy for traders' expectation. Ratio of high price to low price measures the trend of the market. In addition, the international futures price of wheat may have the ability to forecast the Indian wheat futures prices, since Indian commodity futures markets are integrated with the international market after the liberalization and globalization of Indian economy in 1991. We take the futures price of wheat in USA as a measure of international wheat price. Indian commodity futures market is linked to the USA commodity futures market and there is a causal relation from USA wheat futures market to Indian wheat futures market (Kumar and Pandey 2011). Table 3 presents the expected sign of the independent variables.

We have taken the variables with one lag because optimum forecast is based on the formation at time $t-1$. For robustness check, we have compared the forecasting accuracy with ARMA models and Neural Network forecasting technique.

4.2.2. An Autoregressive Moving Average Model

We employ univariate autoregressive moving average (ARMA) models to examine the extent to which the past values of futures prices of wheat can be used to forecast the wheat futures prices. We first fit the best model based on the past data and then make the forecast. Our two best fitted models based on the past data of futures prices of wheat are ARMA (1, 1) and ARMA (1, 2). We have selected the optimal lag length according to the Akaike Information Criterion (AIC) and the Bayesian information criterion (BIC). We estimate the following ARMA (1, 1) model:

$$dlnFP_{wt} = \alpha_0 + \alpha_1 dlnFP_{w(t-1)} + \theta_1 \varepsilon_{t-1} + \varepsilon_t \qquad (2)$$

[8] Futures price gives information about expected spot price. This means that on the expiry of futures contract futures price is equal to spot price, but this may be the Case. There is risk involved with futures market. So. Futures price is equal to expected spot price plus risk premium. Basis is used to measure the risk premium because basis is equal to risk premium plus change in expected spot price and current price.

where α_1 is the autoregressive coefficient. If α_1 is positive and significant, it implies that past values of futures returns of wheat affect positively the current futures returns of wheat. Similarly, if α_1 is negative and significant, it implies that past values of futures returns of wheat affect negatively the current futures returns of wheat. θ_1 refers to the moving average coefficient. If θ_1 is positive and significant, it means that past error (shocks) affects positively the current value of wheat futures. In the same way, if θ_1 is negative and significant, it means that past error (shocks) affects negatively the current value of wheat futures.

In addition, we also estimate the following ARMA (1, 2) model:

$$dlnFP_{wt} = \alpha_0 + \alpha_1 dlnFP_{w(t-1)} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \varepsilon_t \tag{3}$$

where θ_2 is the moving average coefficient of order two. If θ_2 is positive and significant, it means that past error (shocks) two days ago affects positively the current value of wheat futures.

4.2.3. A Neural Network Framework

We employ the Neural Network technique to evaluate the robustness of our forecasting results. A Neural Network framework is a data driven forecasting technique that attempts to capture the underlying complexities while estimating the relationship of interest. It is an improvement over the traditional regression framework in that it is based on less restrictive assumptions and works with more flexible functional forms (Hecht 1990). The functional form need not be linear in a neural network. It is a nonlinear model and is classified as semiparametric (Tsay 2010). It connects the input data to the output via a system of intermediate relationships referred to as neurons, wherein neurons interact with each other. This technique has been widely used in the forecasting literature (Zaremba 1990, Mendelsohn and Stein 1990, Gurunidsky 1993, Misra and Goswami 2014). The forecasts based on neural networks are better than Box-Jenkins (Sharda and Patil 1990). In addition, there are some evidences that has shown that the forecasts based on the neural networks are better that the regression (structural) techniques (Grudnitski and Osburn 1993).

4.2.3.1 Architecture of Artificial neural network (ANN)

The neural network comprises three layers: the input layer, the (hidden) intermediate layer, and the output layer. While the input layer is analogous to the regressor variables in the traditional regression framework, and the output layer corresponds to the regressand, it is the (hidden) intermediate layer that is the distinguishing component of a neural network framework. This intermediate layer tends to get denser and, indeed, multi-layered as the phenomenon of interest (or the data generating process as it were) gets more complicated.

An artificial neural network consists of processing elements, we call it neurons.[9] Each neuron is like a variable. The arrows linking the neurons signify the parameters of neurons (Figure 7). The parameters of the neurons are the weights associated with it. In this technique, we connect the input data to the output data via a system of neurons and these neurons learn from other neurons.

The following are the steps in constructing an artificial neural network. First, we decide the structure of the network which is explained in figure 7. It includes number of input nodes, number of hidden layers and nodes, the transfer function and the output node. The number of input nodes are our lagged explanatory variables such as the gram futures prices, the real rate of interest, the basis defined as the difference between spot and futures prices, and the futures price of wheat in USA, ratio of high price to low price. The first lag of the wheat futures prices is also an explanatory variable. Therefore, the number of input nodes are six. We have one hidden layer (three neurons), and one output node, i.e., the wheat futures prices. The output node is our dependent variable.

Second, we split the data on explanatory variables and dependent variables into two groups. The first group is used to train the network, and the second group is used to validate the network using out of sample forecast. Our sample size is 891. We have used the initial 800 sample points for fitting the network, and remaining 91 sample points to validate the model.

Third, we scale all explanatory variables as well as output variables in the range of 0 to 1. It is required because of the mathematical structure of the network. The rescaling of the data has no impact on the pattern of the data. We rescale the data using the following formula:

[9] The terms neurons and nodes are used interchangeably here.

$$Scaled\ value = \frac{Actual - Minimum}{maximum - Minimum}$$

where

Minimum = Expected minimum value in data

Maximum = Expected maximum value in data.

Fourth, we set the initial training weight and begin a training epoch. An epoch implies the computation of errors and change of weights by processing entire sample in the training data set. In addition, we give initial values to all the weights in the network. The initial weight affects the final solution. The good starting point of the initial weight is unknown. Most programs recommend the randomization of the training weights between -1 and 1 (Delurgio 1998). We have used RATS software, and it determines the initial weight randomly between -1 and 1.

Fifth, we provide the scaled inputs at neurons 0, 1, 2, 3, 4 and 5 (figure 7), and we designate these neurons as I_0, I_1, I_2, I_3, I_4 and I_5, respectively. Generally, we name input node as I_j and output node as O_j. At input layer, there is no transformation of explanatory variables, so output of an input neuron is same as its input value.

Sixth, every neuron in input layer receives its scaled value and transmits it to every neuron in hidden layer. These scaled inputs are weighted and provide input to hidden neurons in step (7). There is parallel processing of inputs at other two hidden neurons. In our network, there is one hidden layer and the hidden layer has three neurons.

Seven, we give weights and sum inputs to receiving nodes[10]. This implies that at every hidden neuron, we give weights to the output of input neurons and sum it. Therefore, the input to neuron 6 is written as:

[10] The summation formula at a neuron is

$$I_j = \sum_{j=f}^{s} W_{ij} O_i$$

where I_j is the inputs (weighted) received by neuron j, W_{ij} is the weight from neuron i to neuron j, O_i is the signal given by neuron j, j is the neuron that receives signal, i the neuron that send signal and f, s are the first and last neurons that send send signals, respectively.

$$I_6 = W_{06}O_0 + W_{16}O_1 + W_{26}O_2 + W_{36}O_3 + W_{46}O_4 + W_{56}O_5$$

We determine the weights and values after several iterations of the training data. The weights are memory and intelligence of the network. They are similar to the coefficients of the regression model. But, weights in neural network are hard to interpret.

Eight, we transform the weighted inputs at each hidden node to outputs ranged from 0 to 1. We employ the logistic function to express the relationship between input and output of neuron. This is a nonlinear transformation[11]. Output at neuron 6 is

$$O_6 = \frac{1}{(1 + e^{-I_6})}$$

where e is the natural number whose value is 2.718…

The output value of O_6 is one input for neuron I_9 (figure 7).

Nine, we weight and add hidden neuron outputs as input to output node. The output neuron is the final neuron. From figure 7

$$I_9 = W_{69}\,O_6 + W_{79}\,O_7 + W_{89}O_8 + \theta_3$$

where θ_3 is the bias of the forecast. It is like a constant term in regression equation.

Ten, we transform the weighted inputs I_9 to output of O_9 ranged from 0 to 1. O_9 is the final output of the neural network. Again we employ the logistic function. Output at neuron 9 is

$$O_9 = \frac{1}{(1 + e^{-I_9})}$$

[11] The transfer function is nonlinear. After we calculate I_j , we send the strength of the incoming signals to the receiving neuron. They then are transformed and becomes outgoing signal to the next layer of neurons. We employ sigmoid function to transform the signal.

$$O_j = \frac{1}{\left(1 + e^{-I_j}\right)}$$

Since the output of the sigmoid transfer function lies between 0 and 1, O_j lies between 0 and 1. High value of I_j implies that O_j will approach to 1. If I_j is very very negative, the O_j will tend to 0.

Eleven, we then calculate errors in the output. We compare the scaled ANN output value O_9 to the true output (scaled) D_9, and compute the error.

$$e_i = D_9 - O_9$$

Where i denotes the observation number in the training data.

Twelve, in this step, there is back propagation of errors, i.e., there is adjustment of weights in the training so as to achieve the minimum residual mean standard error (RMS) value (see appendix B for details on the back propagation of errors). The method of spreading information about errors from the output layer back to hidden layer is termed as back propagation.

Thirteen, we continue the epoch. We once again repeat steps (5) to (12) for all input data.

Fourteen, there is calculation of epoch RMS value. If we get the low[12] value of the RMS, we move to next step, otherwise we repeat the steps (5) to (14).

Fifteen, we validate the ANN results with out of sample data. The model is valid if the training RMS is consistent with out of sample RMS.

Sixteen, we then use the model for forecasting.

4.3. The Data Set

In this study we use daily data that is available six days a week for the period May 21, 2009 to August 28, 2014, drawn from the National Commodity and Derivative Exchange (NCDEX) of India. The data are available from the NCDEX website. We consider the following economic variables: the gram futures prices, the real rate of interest, the basis defined as the difference between spot and futures prices, and the futures price of wheat in USA. The data on traders' expectations about the wheat futures prices are not available, so we use the ratio of high price to low price as a proxy for traders' expectations. We have taken the data on economic variables from various sources in public domain. The data on futures price of gram and basis for wheat are obtained from NCDEX website, rate of interest from reserve bank of India website,

[12] There is convergence of the training data set, and we get the global minimum point of the RMS value.

wholesale price indices from the Office of the Economic Advisor, Government of India, the futures price of wheat in USA from Bloomberg data and consumer price index of USA from federal reserve economic data (FRED). The futures prices of wheat, gram and the futures price of wheat in USA are made inter-temporally comparable by deflating them. We also deseasonalise these prices. Alternative futures contracts for wheat and gram are traded simultaneously on a daily basis. Of these, we chose the so-called 'nearby contract'[13] for our analysis, because it is the most liquid contract of all (Crain and Lee 1996). Figures 1-6 show the evolution of futures price of wheat, futures price of gram, wheat basis, real rate of interest, ratio of high price to low price of wheat futures contract and futures price of wheat in USA, respectively.

Table 1 presents the descriptive statistics of the wheat futures and economic variables in levels and first differences (Panel A and B respectively). The mean returns are positive for all except futures price of wheat in USA. Measuring volatility by standard deviation, we find that it is highest for gram futures (1.097) followed by wheat futures (0.755) and real interest rate (0.403). The lowest volatility is seen in ratio of high price to low price (0.006) and USA wheat futures returns (0.021). The Jarque-Bera test statistics signify that the returns distribution is not normal for most commodities, except the futures returns of gram.

We employ the Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF) and Phillips-Perron tests, and then the Dickey-Fuller generalized least squares (DF-GLS) test proposed by Elliot et al. (1996) for unit root in the in the series. The (DF-GLS) test is a second generation test, and has greater power than the first generation DF, ADF, and PP tests. Since data plots show the deterministic trend and intercept in the series, we assumed deterministic trend and intercept in the DF-GLS test. We report ADF test and DF-GLS test results[14] in table 1. The optimum lag lengths were selected using the Schwarz Criterion. The DF-GLS test and ADF test revealed that the futures prices wheat, gram and futures prices of wheat in USA are non-stationary in levels, so that we work with the log (first) of difference prices (Table 1). The real

[13] The nearby contract is the futures contract whose delivery should be at least one month away.

[14] We have reported the results of two tests, i.e., ADF and DF-GLS tests to validate the presence of unit root in the data series.

rate on interest is non-stationary in levels but stationary in first difference. In addition, the basis and the ratio of high price to low price of wheat futures are stationary in levels.

4.4. Forecast Evaluation

Forecasts are helpful because financial decisions require long term commitment of resources. Any decision taken today has its impact on future. So, knowledge about future is essential in taking any financial decision. An accurate forecast of the futures prices of wheat will help the traders, mill owners, and speculators to make expectation about the subsequent (future) spot prices in a better way.

We started off by asking the question: Can wheat futures prices be forecast? We then developed alternative estimation frameworks to estimate wheat futures prices. We would now like to evaluate the alternative specifications using out-of-sample forecasts. The out-of-sample forecasts are made using only part of the sample to estimate the model parameters, and forecasting on the basis of these parameter estimates. These forecasts can then be evaluated by comparing them to the sample observations which were not used for estimation. For instance, we estimate the four alternative specifications using the sample observations spanning 21 May 2009 to 4 March 2014, and obtain the 'first' out-of-sample forecast for 5 March 2014. Enlarging the sample by one day, i.e. using the sample for 21 May 2009–5 March 2014, we re-estimate the four alternative specifications, and obtain the 'second' forecast for 6 March 2014. And so on, until we have used up all the sample observations but one. Given our sample period from 21 May 2009 to 28 August 2014, we begin this exercise with the estimation sample spanning the period 21 May 2009 to 4 March 2014. The subset[15] from 5 March 2014 to 28 August 2014, is used for the out-of-sample forecast evaluation.

[15] Another way to generate forecast is the in-sample forecasts for the alternative specifications. In-sample forecasts are made using all the observations that we used for estimating the forecast model parameters. Nevertheless, a practical approach to the model evaluation through examination of forecast accuracy is not to use entire observations in estimating the forecast model parameters, but rather to hold some observations back. The latter sample is used to construct out of sample forecasts.

4.4.1. Forecast Evaluation Criteria

The forecasts from different models are not the same, so that we need to decide which of the models give the most precise predictions. In order to evaluate the forecast accuracy, we employ three alternative metrics, viz., Theil's U-statistic, the Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE).

Theil's U-statistic is a measure of relative forecast accuracy and is unit free. It is defined as the ratio of the root mean squared error of a given forecast model to the root mean square error of the random walk model, where the latter is expressed as:

$$FP_t = FP_{t-1} + \varepsilon_t$$

where ε_t is the white noise process with $E(\varepsilon_t) = 0$ for all t, $V(\varepsilon_t) = E(\varepsilon_t^2) = \sigma^2$ for all t, and $C(\varepsilon_t, \varepsilon_{t-s}) = E(\varepsilon_t, \varepsilon_{t-s}) = 0$ for all t, s. If this test statistic is found to be less (more) than 1, that implies that the forecast model in question is superior (inferior) to a naïve forecast based on the random walk; whereas a test statistic value equal to 1 implies that the forecast based on the specification in question is no better than naïve forecast. The limitation of this statistic is that it does not compare the forecasts amongst alternative specifications. It only makes the comparison of the forecast value of a given model with that of the random walk model (Dua et al. 1993).

The root mean squared error (RMSE) provides an estimate of the average deviation of the actual wheat futures price from the forecast wheat futures price. It is computed as:

$$RMSE = \sqrt{\frac{\sum_{h=1}^{H}(\widehat{FP}_{T+h} - FP_{T+h})^2}{H}}$$

where $\widehat{FP}$ is the forecast value of the futures price of wheat, FP is the actual futures prices of wheat and H is the number of days over which we have evaluated the forecast performance or the forecast horizon. Using data for time period $1\ to\ T$, we make predictions for time point $T + h$, where h is 1 period or more.

The third evaluation criterion is the mean absolute error (MAE), where the error refers to the difference between the actual and forecast wheat futures prices. It is computed as:

$$MAE = \frac{\sum_{h=1}^{H} |\widehat{FP}_{T+h} - FP_{T+h}|}{H}$$

We then compare the forecasts obtained from different models using RMSE and MAE metrics to the forecasts obtained from random walk model because random walk model is the benchmark model. The one period ahead forecast[16] from random walk model is

$$\widehat{FP}_{T+1} = E(FP_{T+1} + \varepsilon_{T+1}) = FP_T$$

In the same way, the h-step ahead forecast from random walk model

$$\widehat{FP}_{T+1} = E(FP_{T+h} + \varepsilon_{T+h}) = FP_T$$

The random walk forecast is called as naïve forecast implying no change forecast (Dua et al. 2003).

There are several methods to check whether the root mean squared error and the mean absolute error from one model is statistically different from the other. These methods are F test, Granger- Newbold test and the Diebold Marino test. F-test is based on the following three assumptions. First, forecast errors should be normally distributed with mean zero. Second, the forecast errors should not be serially correlated. Finally, the forecast errors from the two models should not be contemporaneously correlated. The above three assumptions are highly unrealistic[17], so we do not consider F-test. The Granger-Newbold test overcomes the issue of contemporaneously correlated prediction errors, however this test is still based on the first two unrealistic assumptions. Diebold and Mariano (1995) test is a more robust test because it relaxes all three above mentioned assumptions. We, therefore, prefer Diebold and Mariano (1995) test to check whether the root mean square error of the selected model is statistically different from the random walk model (benchmark model). To illustrate, the Diebold-Mariano test is described as follows:

Our observed data series is $FP_1, FP_2, \ldots, FP_T$ and we make forecasts of the future value of the data series $FP_{T+1}, FP_{T+2}, \ldots, FP_{T+h}$

We define the forecast error as

$$e^i_{T+h} = \widehat{FP}^i_{T+h} - FP_{T+h}$$

[16] Details of the forecasting method for a random walk model are provided in appendix A.

[17] In multistep-ahead forecast, predictions errors may be serially correlated, and the prediction errors from two different models are highly correlated with one another.

where $\widehat{FP}$ is the forecasted value of the futures price of wheat, FP is the actual futures prices of wheat, h is the forecast horizon and $i = 1$ (economic variable model), 2 (ARMA (1,1) model, 3 (ARMA (1,2) model and 4 (neural network technique).

We denote the loss function as $g(e^{i}_{T+h})$. This is the loss related to forecast from model i, and the assumption is that the loss depends on forecast error e^{i}_{t}. The loss function value is zero when there is no forecast error; that is, it never becomes negative. The loss function is generally the square (squared-error loss) or the absolute value (absolute error loss) of the forecast error.

We define $g(e^{i}_{T+h})$ and $g(e^{RW}_{T+h})$ as loss functions from model i and the random walk model, respectively. We denote differential loss function as

$$d_t = g\left(e^{i}_{T+h}\right) - g(e^{RW}_{T+h})$$

We obtain the mean loss function as follows:

$$\bar{d} = \frac{\sum_{h=1}^{H}(g\left(e^{i}_{T+h}\right) - g(e^{RW}_{T+h}))}{H}$$

We then calculate the ratio $\bar{d} \big/ \sqrt{var(\bar{d})}$. This ratio follows standard normal distribution. The null hypothesis under the Diebold Mariano test is that the random walk model and the model under consideration perform equally well. The alternate hypothesis is that the random walk model outperforms the model under consideration.

4.5. Estimation results

To examine the evidence of statistically predictable pattern in the evolution of wheat futures prices, we start off by removing the impact of inflation, trend and seasonality of the futures prices of wheat and other explanatory variables viz., futures price of gram, USA wheat futures price. We use seasonal dummies to check the presence of the seasonal effect. However, we do not find any seasonal impact in the futures price for wheat and gram.

We then estimate the economic variable model. In this model, we have taken the futures prices of wheat as a function its own past, lagged economic factors (Grudnitski and Osburn 1993). We estimate the economic variable model by OLS. Table 3 presents the results of the economics variable model for wheat futures returns for the sample period May 21, 2009 to March 4, 2014. We report the estimated coefficients, standard errors, R^2 and F-statistic value for wheat futures returns. ***, **, and * indicate statistical significance of the estimated parameters at the 1%, 5% and 10% levels, respectively. We find that the value of R^2 is 0.9 %. The value of R^2 obtained in our economic variable model is similar to the earlier studies in several futures markets (Konstantinidi et al. 2008, Miffre 2001, Konstantinidi and Skiadopoulos 2011).

Our results show that the futures returns of wheat in USA and ratio of high price to low price have positive and significant effect on the futures returns of wheat in India. The futures returns of wheat in USA coefficient is 3.162 which is significant at 5 percent level of significance. It suggests that if the returns on futures contract of wheat in USA increases by 1 per cent, then the returns on futures contract of wheat in India increases by about 3.2 percent. This is due to the wide-ranging economic reforms that have taken place in India subsequent to the economic crisis of 1991, resulting in increasing liberalisation and globalisation of markets and removal of state controls. These economics reforms have led to the integration of Indian economy with the international market.

We also find that ratio of high price to low price coefficient is 7.176 which is significant at 10 percent level of significance. It suggests that if the ratio of high price to low price increases by one, then the returns on futures contract of wheat in India increases by about 7.2 percent. We have employed ratio of high price to low price as proxy for and traders' expectations about the futures prices. It measures the trend of the market. High value of the ratio of high price to low price implies that the market is in upward trend. It indicates that more and more new market participants will enter the market. The other explanatory variables included in the model are first lag of futures returns of wheat, futures returns of gram, the real rate of interest and basis, and these variables are not significant[18]. However, the sign of their coefficients are as expected. The F-statistic of the economic variable model is 2.289, implying that it is significant at 5 percent level of significance.

We followed the Box-Jenkins modelling procedure to estimate the futures returns of wheat for the sample period May 21, 2009 to March 4, 2014. The ARMA (1, 1) and ARMA

[18] We are not concerned about the significance of individual explanatory variables in forecasting literature. However, we are concerned with significance of the model and forecast accuracy.

(1, 2) are the two best fitted models.[19] Tables 4A and 4B present the results of the ARMA (1, 1) and ARMA (1, 2) models for wheat futures respectively.

We find that the values of R^2 in case of ARMA (1, 1) and ARMA (1, 2) are 0.40 and 0.50, respectively. Considering the ARMA (1, 1) model first, we find that the autoregressive coefficient α_1 is positive and significant. This implies that the past values of futures returns of wheat affect positively the current value of wheat futures returns. We also find that the moving average (MA) coefficient θ_1 is negative and significant at 5 percent level of significance. This means that the past error affects negatively the current value of wheat futures returns. Similarly, in the ARMA (1, 2) model, we find that the autoregressive coefficient and the moving average coefficient of order one are significant. However, the moving average coefficient of order two (θ_2) is not significant.

Next, we are going to assess the out of sample forecast performance of the wheat futures. We will compare the out of sample forecast performance from the economic variable model, ARMA (1, 1), ARMA (1, 2), random walk and neural network.

4.5.1. Point Forecast: Results

We have estimated the models recursively for the period March 5, 2014 to August 28, 2014 and generated the out of sample forecasts. We have employed Theil's U-statistic to measure the forecast accuracy. Theil's U-statistic for economic variable model, ARMA (1, 1), ARMA (1, 2) and the neural network technique is 1.022, 1.004, 1.005 and 1.031, respectively (Table 4A) . We find that Theil's U-statistic is more than 1 for all the four models, implying that the naïve forecast is better than the model forecasts (Dua et al. 1993). However, Theil's U-statistic is influenced by the mean squared error of the naïve forecast. Therefore, to check forecast accuracy we have also used RMSE and MAE (Dua et al. 1993). The model that gives the most accurate forecast will have the smallest value of RMSE and MAE.

Table 5 presents the values of RMSE and MAE for the economic variable model, ARMA (1, 1), ARMA (1, 2), random walk and neural network. Considering the RMSE first, we find that the estimated value of RMSE for the economic variable model, ARMA (1, 1), ARMA (1, 2), neural network and random walk are 0.7101, 0.6975, 0.6986, 0.7169 and 0.6948, respectively. The random walk model has the smallest value of RMSE. The result from RMSE

[19] We have selected the two best fitted models because the first best model may not give the most accurate forecast.

suggests that the random walk model appears to outperform all other four models employed our study. With regard to the MAE, we find that the estimated value of RMSE for the economic variable model, ARMA (1, 1), ARMA (1, 2), neural network and random walk are 0.4766, 0.4673, 0.4678, 0.4999 and 0.4673, respectively. The random walk model has the smallest value of MAE. On the basis of RMSE and MAE, the random walk model gives the most precise predictions of the wheat futures returns.

Next, we have employed the Diebold-Mariano (DM) test to examine whether the RMSE and MAE from the model under consideration is statistically different from the random walk model (the benchmark model). Table 5 presents the results of the Diebold-Mariano (DM) test of out of sample forecast of model specification.

The null hypothesis in this test is that the random walk model and the model under consideration perform equally well. ***, **, and * indicate the rejection of null hypothesis in favour of alternative hypothesis at the 1%, 5% and 10% levels, respectively, by DM test. The alternate hypothesis is that the random walk model outperforms the model under consideration. Considering the RMSE first, the DM test statistic suggest that the null hypothesis is rejected for economic variable model, ARMA (1, 2) and neural network. It implies that the random walk model is a better predictor than for economic variable model, ARMA (1, 2) and neural network. However, there is no difference in forecasting accuracy between the ARMA (1, 1) and the random walk model. With regard to the MAE, the DM test statistic suggest that the null hypothesis is rejected for economic variable model, ARMA (1, 1), ARMA (1, 2) and neural network. It implies that the random walk model is a better predictor than for economic variable model, ARMA (1, 1), ARMA(1, 2) and neural network. So, we conclude that the random walk has the best forecasting performance, and random walk beats all the four models considered. This implies that the futures price of wheat cannot be forecasted,[20] and wheat futures market is efficient.

Unfortunately, we cannot compare our results to other studies for India simply because there aren't any. However, we compare our results with the studies of other countries, because the similar factors affect futures prices in other countries as well. The findings of this study are consistent with previous findings of Hartzmark (1987), Hartznark (1991), Konstantinidi etal. (2008) and Konstantinidi and Skiadopolous (2011). Hartzmark (1987) using the daily data

[20] Based on the models that we have selected.

found that speculators do not gain much from commodity and interest rate futures contacts. Hartznark (1991) attributed the source of profit to luck rather than better predicting ability of the market participant, and concluded that the commodity and financial futures markets were efficient. Konstantinidi et al. (2008) have investigated the efficiency of volatility index futures indirectly. They have taken the daily data for the period February 2, 2001 to September 28, 2007 from European and US implied volatility indices, and found that volatility futures markets are efficient. Konstantinidi and Skiadopolous (2011) have examined whether volatility futures prices per se can be predicted. They have taken the daily data of volatility index futures and several economics variables affecting the volatility index. They employ the data from Chicago board of trade for the period March 26, 2004 to March 13, 2008. Their study found that the volatility futures index cannot be forecasted, and the market is efficient.

However, the findings of this study differ from the findings of Yoo and Maddala (1991, Bassembinder and Chan (1992), Miffre (2002). Yoo and Maddala (1991) examined the commodity and currency futures using the daily data, and found that speculators on an average make profit. They have taken the data from Chicago board of trade for the period January 1976 to December, 1984. Bassembinder and Chan (1992) found that commodity futures returns can be predicted. They have used the Chicago board of trade data, and concluded that instrumental variables (treasury bill yields, equity dividend yields etc.) possess the predicting power for agricultural futures returns. Miffre (2002) study has shown the similar findings for commodity futures contracts respectively. However, Yoo and Maddala (1991) and Miffre (2002) and discovered that the market participants' profit from trading in futures contract were not abnormal.

4.6. Conclusions and Policy Implications

Using daily data on futures price for wheat, futures price for barley, the real rate of interest, the basis, the futures price of wheat in USA and traders' expectations about the futures prices of wheat, this study, for the first time, examines whether Indian wheat commodity futures prices per se can be forecasted. We employ several alternative model specifications, viz. the economic variable model, ARMA (1, 1), ARMA(1, 2) and Neural network techniques etc. We compare the out of sample forecast performance from each of the four models with the random walk (bench mark) model.

We construct the point forecasts and evaluate their statistical significance using the Diebold-Mariano test. In order to make point forecast, we estimate all the four models for the in sample period (from May 21, 2009 to March 4, 2014), and we got the first out of sample forecast (that corresponds to March 5, 2015). We have used the recursive forecasting approach to generate the remaining out of sample point forecasts. Given our sample period from 21 May 2009 to 28 August 2014, we begin this exercise with the estimation sample spanning the period 21 May 2009 to 4 March 2014. The subset from 5 March 2014 to 28 August 2014, is used for the out of sample forecast evaluation.

The statistical significance of out of sample forecasts suggests that none of the models selected in the study have forecasting power in predicting wheat futures returns. The random walk has the best forecasting performance. Hence, the hypothesis that the wheat futures market is informationally efficient cannot be rejected. Our results imply that Indian wheat commodity futures prices per se cannot be forecast. Nonetheless, it has been established that the wheat commodity futures market is efficient, which does not invalidate trading of wheat futures on national exchanges. This is because wheat commodity futures can be used to hedge against change in commodity spot prices. Risk management through hedging is an important function of futures market (Edward and Ma 2003, Choudhary 2009). In addition, fundamental view holders who make their decisions based on demand and supply of the underlying commodity, will trade in the wheat futures market to earn profits from the market.

These results lead us to opine, that the Indian authorities need to start awareness programme among the farmers (and other market participants) about the benefits of futures market. The futures price of wheat cannot be forecast. It implies that wheat futures market is efficient and it strengthens our claim that the Indian commodity wheat futures market is performing its economic role of price discovery and risk management through hedging.

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Table 1: Summary statistics

	Wheat FP	Gram FP	Real interest rate	USA wheat FP	Basis	Ratio of high to low price
Panel A: Summary statistics of wheat futures prices and economic variables						
Mean	3.128	3.476	-0.488	11.709	0.015	1.009
Maximum	3.225	3.702	6.410	12.160	0.186	1.043
Minimum	3.033	3.310	-8.080	11.210	-0.089	1.000
Standard Deviation	0.055	0.093	2.997	0.227	0.041	0.006
Skewness	0.230	0.368	-0.549	-0.412	1.201	1.796
Kurtosis			2.387	2.390	4.419	7.545
Jarque-Bera statistic	137.280***	52.704***	113.146***	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***
Panel B: Summary statistics of wheat futures prices and economic variables (first difference)						
Mean	0.036	0.004	0.075	-0.001		
Maximum	3.166	2.989	4.020	0.089		
Minimum	-4.316	-2.989	-3.200	-0.097		
Standard Deviation	0.755	1.097	0.403	0.021		
Skewness	0.073	0.037	3.039	0.133		
Kurtosis	6.370	2.893	29.246	5.107		
Jarque-Bera statistic	423.033***	0.636	26977.800***	167.764***		
ADF	-38.144***	-35.984***	-26.392***	-37.681***		
DF-GLS	-13.402***	-35.826***	-3.146**	-12.544***		
Observations	892	892	892	892	892	892

Notes: FP - futures price. ADF – Augmented Dickey Fuller, DF-GLS - Dickey Fuller generalized least square.
***, **, * denotes significance at 1%, 5%, 10% level implying that the null hypothesis is rejected.
The null hypothesis for the Jarque-Bera test is that the data has normal distribution.
The null hypothesis for the ADF and DF-GLS test is that the series has a unit root.

Table 2: Economic variable model

Variable	Coeff.
Constant	-7.209*
	(4.284)
$FP_{w(t-1)}$	0.032
	(0.035)
$FP_{g(t-1)}$	-0.033
	(0.024)
i_{t-1}	-0.086
	(0.076)
$basis_{t-1}$	-0.129
	(0.647)
$FP_{US\_w(t-1)}$	3.162**
	(1.236)
R_{t-1}	7.176*
	(4.206)
R^2	0.010
Obs.	800

Notes: We estimate the following equation:

$$FP_{wt} = C + \alpha_1 FP_{w(t-1)} + \alpha_2 FP_{g(t-1)} + \alpha_3 i_{t-1} + \alpha_4 basis_{t-1} + \alpha_5 FP_{US\_w(t-1)} + \alpha_6 R_{t-1} + \varepsilon_t,$$

FP_w denotes the futures price of wheat, FP_g is the futures price of wheat, i refers to the real rate of interest, $basis$ is the difference between spot and futures price of wheat, FP_{US_w} is the futures price of wheat in USA, R is the ratio of high price to low price of wheat futures.

Regression $F(6, 792) = 2.289$ (P-value $= 0.033$).

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

Standard errors are reported in parentheses.

We have estimated the model for the period May 21, 2009 to March 4, 2014.

Table 3: Variables definition and expected sign

Variable	Definition	Expected sign	Source
FP_w	Futures price of wheat	-	
FP_g	Futures price of gram	+/-	Malliaris and Urrutia (1996)
i	Real rate of interest	-	Konstantinidi & Skiadopoulos (2011)
Basis	Basis	-	
FP_{US_w}	Futures price of wheat in USA	+	Kumar and Pandey (2011)
R	Ratio of high price to low price of wheat futures	+	Delurgio 1998

Table 4: Forecasting with univariate ARMA

Panel A ARMA(1,1) model		Panel B ARMA(1,2) model	
C	0.032	C	0.316
	(0.030)		(0.308)
α_1	0.680***	α_1	0.630**
	(0.250)		(0.301)
θ_1	-0.636**	θ_1	-0.598**
	(0.263)		(0.302)
		θ_2	0.022
			(0.041)
Obs.	800	Obs.	800
R^2	0.004	R^2	0.005

Notes: Panel A is ARMA(1,1) model, namely $FP_{wt} = C + \alpha_1 FP_{w(t-1)} + \theta_1 \varepsilon_{t-1} + \varepsilon_t$,
Panel B is ARMA(1,2) model $FP_{wt} = C + \alpha_1 FP_{w(t-1)} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \varepsilon_t$
***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.
Standard errors are reported in parentheses.
We have estimated the model for the period May 21, 2009 to March 4, 2014.

Table 5: Out of sample performance of the model specification for wheat futures price series

	RW	Economic Model	ARMA(1,1)	ARMA(1,2	Artificial Neural Network
RMSE	0.6948	0.7101	0.6975	0.6986	0.7169
MAE	0.4627	0.4766	0.4673	0.4678	0.4999
Theil's U		1.022	1.003	1.005	1.031

Notes: RMSE - root mean square error, MAE - mean absolute error, and RW - random walk
We have estimated the model recursively for the period March 5, 2014 to August 28, 2014

Table 6: Diebold-Mariano test of forecast accuracy

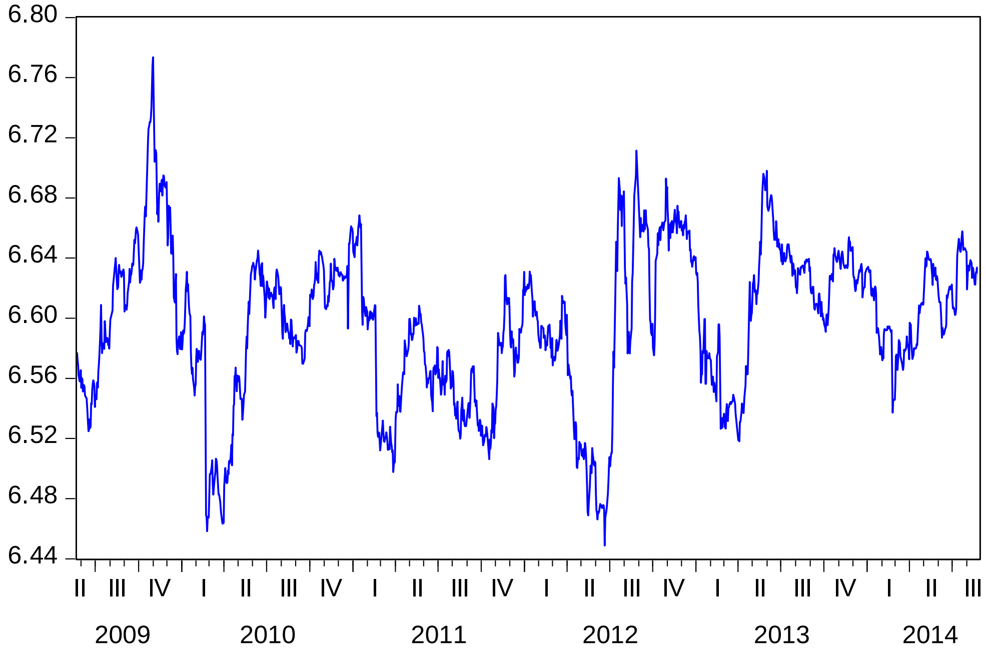
H_0: RW and the model under consideration perform equally well
H_1: RW outperforms the model

	RW	Economic Model	ARMA(1,1)	ARMA(1,2	Artificial Neural Network
RMSE	0.6948	0.7101*	0.6975	0.6986*	0.7169*
MAE	0.4627	0.4766**	0.4673*	0.4678*	0.4999***

Notes: ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.
RMSE - root mean square error, MAE - mean absolute error, and RW - random walk
We have estimated the model recursively for the period March 5, 2014 to August 28, 2014

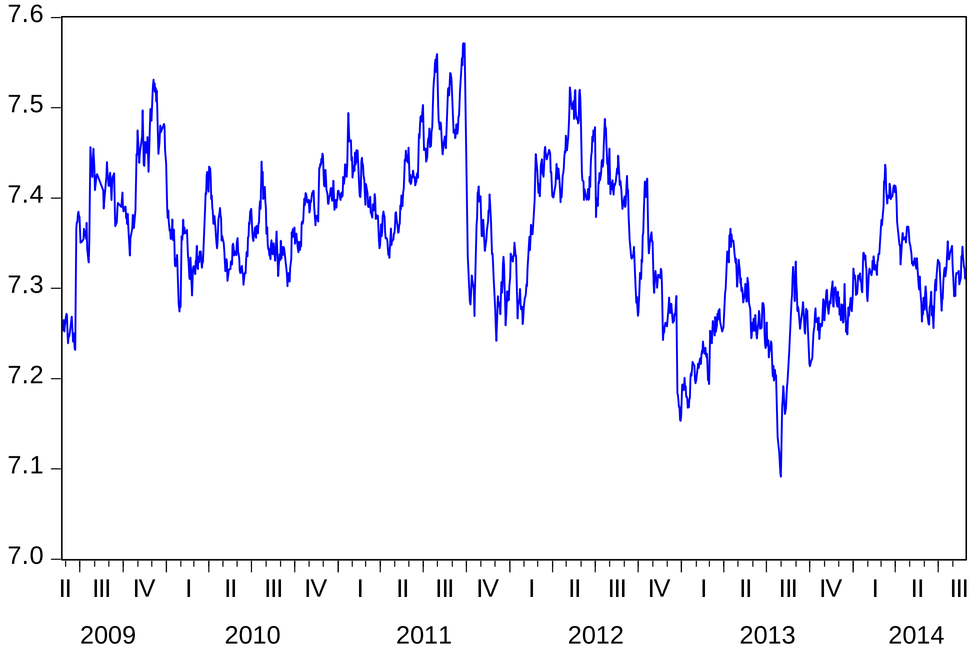
Graphs

Figure 1. Wheat: daily futures price, 2009-2014



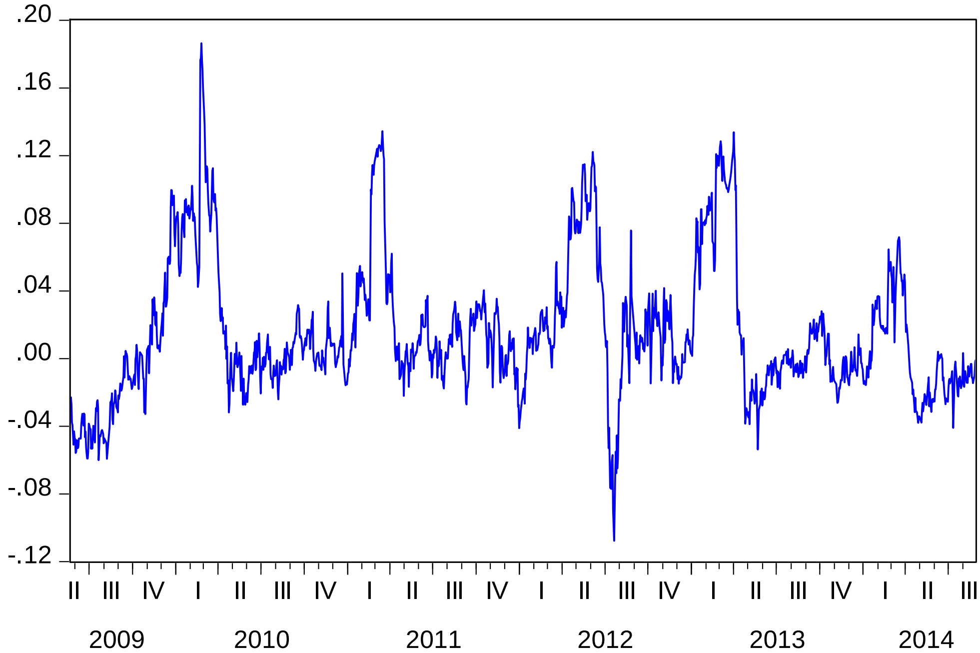
Source: Author's estimation based on secondary data from the National Commodity and Derivative Exchange (NCDEX), Mumbai, and the Multi-Commodity Exchange (MCX), Mumbai.
Notes: Wheat futures price is in log. Period of analysis: May 2009 – August 2014(daily data).

Figure 2. Gram: daily futures price, 2009-2014



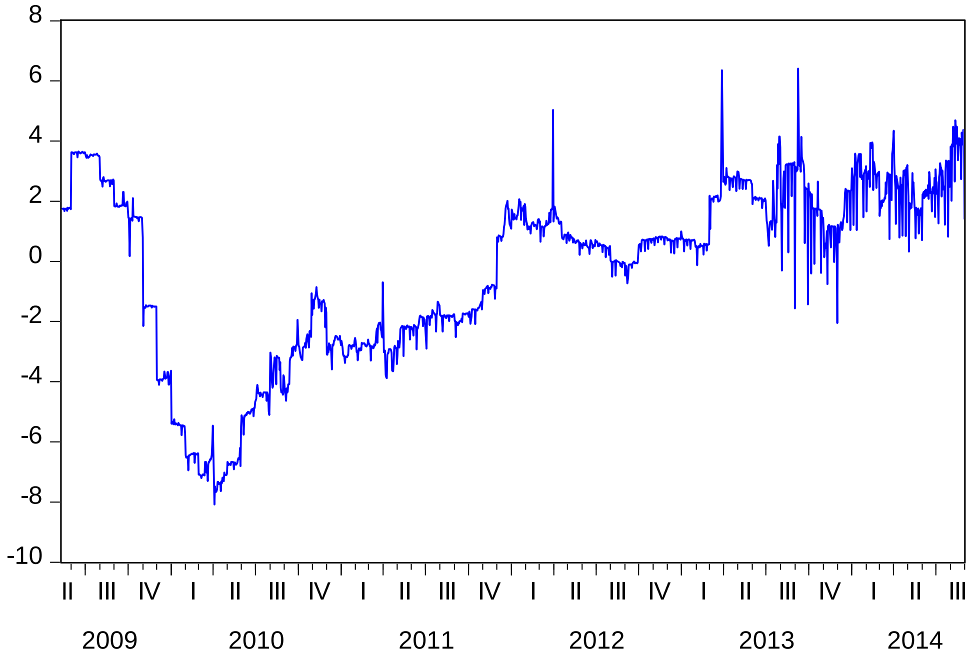
Source: Author's estimation based on secondary data from the National Commodity and Derivative Exchange (NCDEX), Mumbai, and the Multi-Commodity Exchange (MCX), Mumbai.
Notes: Gram futures price is in log. Period of analysis: May 2009 – August 2014(daily data).

Figure 3. Wheat basis (daily), 2009-2014



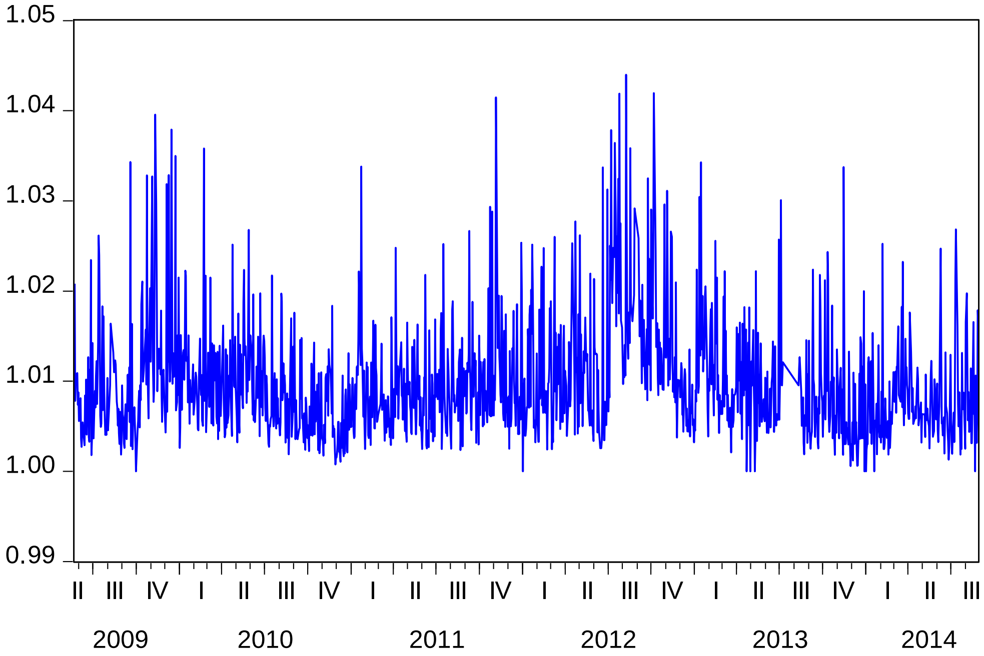
Source: Author's estimation based on secondary data from the National Commodity and Derivative Exchange (NCDEX), Mumbai, and the Multi-Commodity Exchange (MCX), Mumbai.
Notes: Wheat basis is in log. Period of analysis: May 2009 – August 2014(daily data).

Figure 4. Real interest rate (daily), 2009-2014



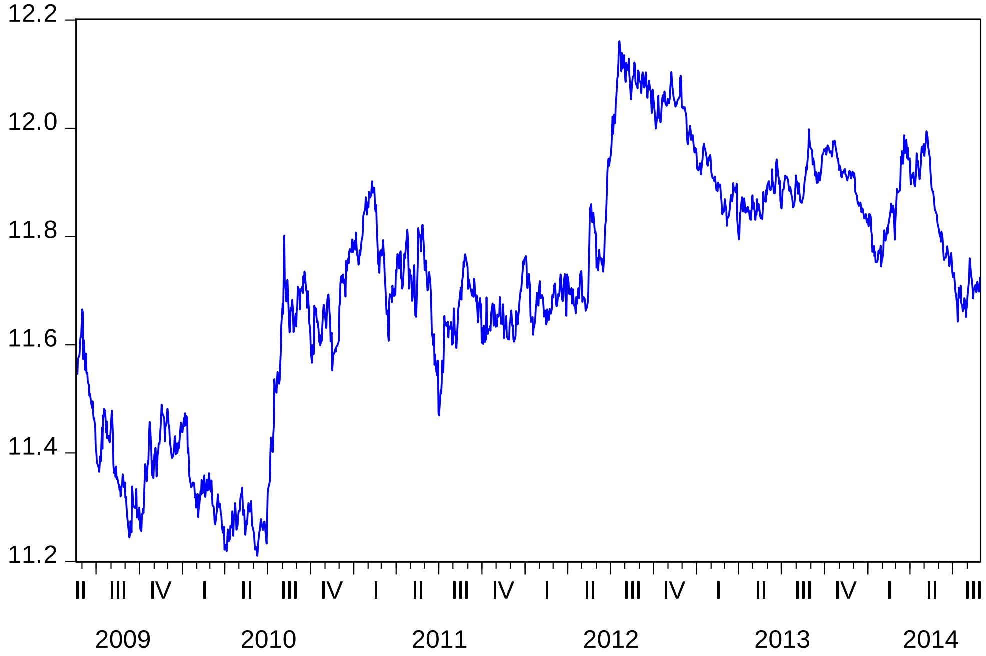
Source: Author's estimation based on secondary data from the reserve bank of India website.
Notes: Period of analysis: May 2009 – August 2014(daily data).

Figure 5. Ratio of high to low price of wheat futures (daily), 2009-2014



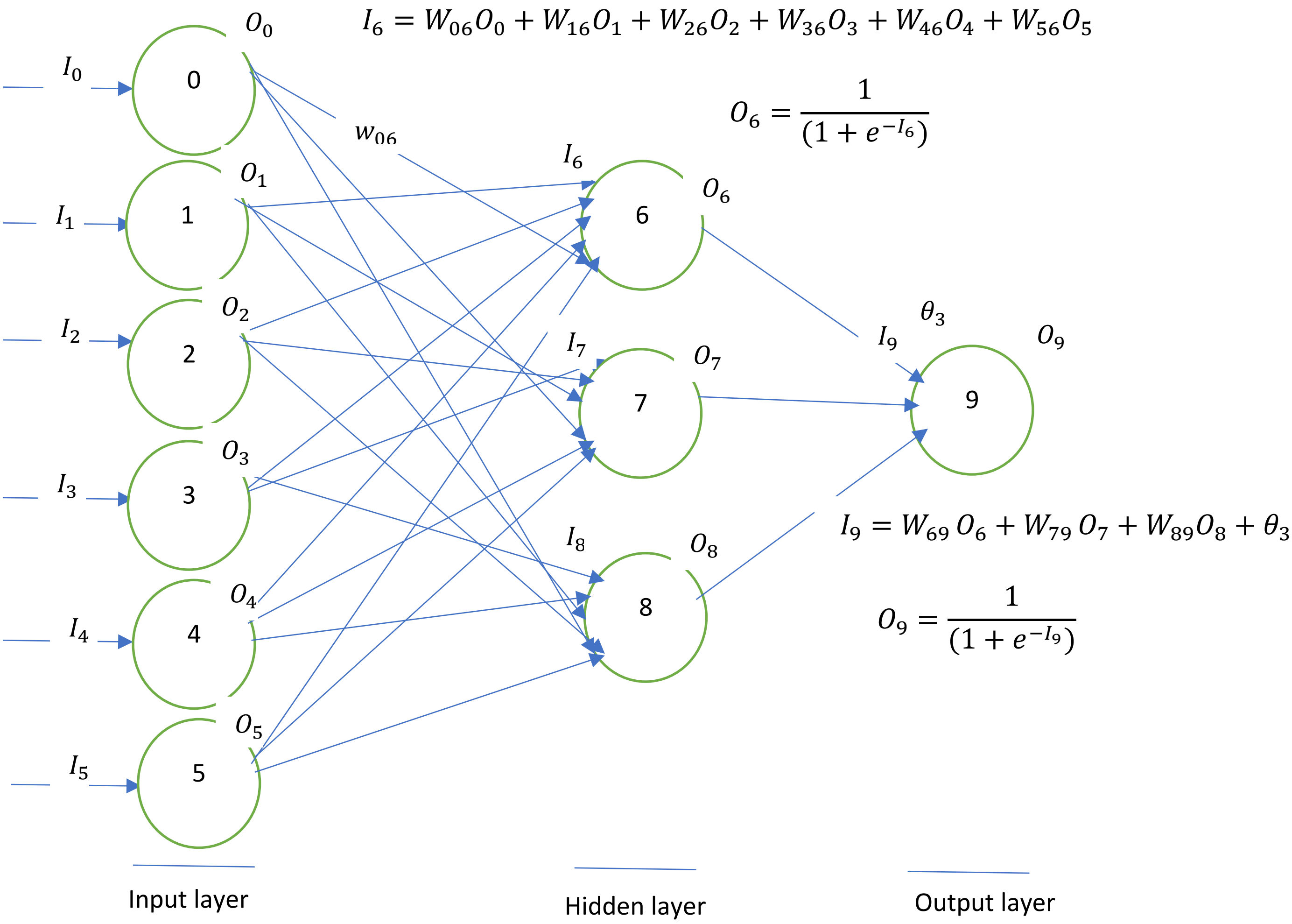
Source: Author's estimation based on secondary data from the National Commodity and Derivative Exchange (NCDEX), Mumbai, and the Multi-Commodity Exchange (MCX), Mumbai.
Notes: Period of analysis: May 2009 – August 2014(daily data).

Figure 6. USA wheat: daily futures price, 2009-2014



Source: Author's estimation based on secondary data from the Bloomberg database.
Notes: Futures price of wheat in USA is in log. Period of analysis: May 2009 – August 2014(daily data).

Figure 7: Artificial Neural Network



I_o = $wheat\ futures\ price_{t-1}$

I_1 = $gram\ futures\ price_{t-1}$

I_2 = $real\ rate\ on\ interest_{t-1}$

I_3 = $basis_{t-1}$

I_4 = $USA\ wheat\ futures\ price_{t-1}$

I_5 = $\frac{wheat\ futures\ high_{t-1}}{wheat\ futures\ low_{t-1}}$

Appendix A

Forecasting in auto regressive (AR) models

Our observed data series is FP_1, FP_2, …, FP_T and we make forecasts of the future value of the data series FP_{T+1}, FP_{T+2}, …, FP_{T+h}

we define $fp_T = [FP_1, FP_2, \dots, FP_T]'$, and h is the forecast horizon. We also define

$\widehat{FP}_{T+h} |\, fp_T$ as the forecasted value of FP_{T+h}, conditioned on the value of fp_T. The information is available only till time T.

We write prediction error as $FP_{T+h} - \widehat{FP}_{T+h} |\, fp_T$. We also write $\widehat{FP}_{T+h} |\, fp_T$ as $\widehat{FP}_{T+h} |\, T$

Now, we can rewrite the prediction error into two terms:

$$FP_{T+h} - \widehat{FP}_{T+h}|T = \{FP_{T+h} - E(FP_{T+h}|T)\} + \left\{E(FP_{T+h}|T) - \widehat{FP}_{T+h}|\mathrm{T}\right\}$$

The forecast mean square error (MSE) can be written as:

$$MSE\left(\widehat{FP}_{T+h}|\mathrm{T}\right) = E(FP_{T+h} - \widehat{FP}_{T+h}|\mathrm{T})^2$$

$$= E(\left[\{FP_{T+h} - E(FP_{T+h}|T)\} + \left\{E(FP_{T+h}|T) - \widehat{FP}_{T+h}|\mathrm{T}\right\}\right]^2)$$

By expanding the above equation, we find that some terms become zero (Leybourne 2010; Enders 2014; Brooks 2014).

Therefore, we get

$$MSE\left(\widehat{FP}_{T+h}|\mathrm{T}\right) = Var\,(FP_{T+h}|T) + E[\{E(FP_{T+h}|T) - \widehat{FP}_{T+h}|\mathrm{T}\}^2]$$

This will be minimum if

$$\widehat{FP}_{T+h}|T = E(FP_{T+h}|T)$$

Thus, we conclude that the optimum forecast of FP_{T+h} is the condition mean of FP_{T+h}. In addition, its forecast mean square error is $Var\,(FP_{T+h}|T)$, which is the conditional variance of FP_{T+h}.

Now, we take the stationary AR (1) process

$$FP_t = \alpha FP_{t-1} + \varepsilon_t$$

We examine one step forecast now

$$FP_{T+1} = \alpha FP_T + \varepsilon_{T+1}$$

$$\widehat{FP}_{T+1}|T = E(FP_{T+1}|T)$$

$$= E(\alpha FP_T + \varepsilon_{T+1}|T)$$

$$= \alpha E(FP_T|T) + E(\varepsilon_{T+1}|T)$$

$$= \alpha FP_T + 0$$

$$= \alpha FP_T$$

Consider two step forecast,

$$FP_{T+2} = \alpha FP_{T+1} + \varepsilon_{T+2}$$

$$\widehat{FP}_{T+2}|T = E(FP_{T+2}|T)$$

$$= E(\alpha FP_{T+1} + \varepsilon_{T+2}|T)$$

$$= \alpha E(FP_{T+1}|T) + E(\varepsilon_{T+2}|T)$$

$$= \alpha . \alpha FP_T + 0$$

$$= \alpha^2 FP_T$$

Consider two step forecast

$$FP_{T+3} = \alpha FP_{T+2} + \varepsilon_{T+2}$$

$$\widehat{FP}_{T+3}|T = E(FP_{T+3}|T)$$

$$= E(\alpha FP_{T+2} + \varepsilon_{T+3}|T)$$

$$= \alpha E(FP_{T+2}|T) + E(\varepsilon_{T+3}|T$$

$$= \alpha . \alpha^2 FP_T + 0$$

$$= \alpha^3 FP_T$$

We, therefore, conclude that

$$\widehat{FP}_{T+h}|T = \alpha^h FP_T$$

We find that in case of random walk process $\alpha = 1$. Thus, for a random walk

$$\widehat{FP}_{T+h}|T = FP_T$$

We, therefore, call the random walk forecast as no change forecast (Dua et al. 2003).

Appendix B

Backpropagation of neural network (Delurgio 1998)

The method of spreading information about error from the output layer back to hidden layer is termed as back propagation. The assumption under the back propagation of a neural network is supervision of the training of input data set. The weights (W) are adjusted to minimize the sum of the squares errors of the training input data. We define j a receiving neuron, and i aneuron that feed that neuron (input or hidden).

At every noninput neuron, output is O_j

$$O_j = \frac{1}{\left(1+e^{-I_j}\right)} \tag{B 1}$$

$$I_j = \sum W_{ij} O_i \tag{B 2}$$

where O_i is one of the signals to neuron j. We can say that neuron j is the output of neuron i.

we employ chain rule of the partial derivatives to derive the formula of back propagation.

$$\delta_{ij} = \frac{\partial SSE}{\partial W_{ij}} = \left(\frac{\partial SSE}{\partial O_j}\right)\left(\frac{\partial O_j}{\partial I_j}\right)\left(\frac{\partial I_j}{\partial W_{ij}}\right) \tag{B 3}$$

δ_{ij} is the change in sum of squared error due to change in weight W_{ij}

$$\text{Now } e_i = \left(D_j - O_j\right) \tag{B 4}$$

where D_j is the true output (scaled) and O_j is the ANN output.

$$SSE = \sum\left(D_j - O_j\right)^2 \tag{B 5}$$

$$\left(\frac{\partial SSE}{\partial O_j}\right) = -2\sum\left(D_j - O_j\right) \tag{B 6}$$

output at output neuron will be

$$O_j = \frac{1}{\left(1+e^{-I_j}\right)} \tag{B 7}$$

$$\left(\frac{\partial O_j}{\partial I_j}\right) = O_j\left(1 - O_j\right) \tag{B 8}$$

Input provided to output neuron is

$$I_j = \sum W_{ij} O_i \quad \text{(B 9)}$$

and

$$\left(\frac{\partial I_j}{\partial W_{ij}}\right) = O_i \quad \text{(B 10)}$$

Thus, equation (3) can be rewritten (Delurgio 1998) as

$$\delta_{ij} = 2e_j O_j \left(1 - O_j\right) O_i \quad \text{(B 11)}$$

Now we update old weight by the using the equation below:

$$\Delta W_{ij}(new) = \alpha \Delta W_{ij}(old) + \eta \delta_{ij} O_j \quad \text{(B 12)}$$

where η is the learning rate and that is fixed between 0 and 1, δ_{ij} is the change in the sum of squared errors with respect to weight at a neuron and is also called as the neuron's share of the error, O_j is the output at neuron j, $\Delta W_{ij}(old)$ is the change made in weight W_{ij}in previous epoch, α is the momentum coefficient lying between 0 and 1. We incorporate momentum coefficient alpha in the generalized delta rule to prevent local minima, and to reduce the number of training epochs.

The above equation (B 12) is called as the generalized delta rule. It implies that the change in weight in the ANN from neuron i to neuron j is η times output neuron share of the total error, δ_{ij} times the output (O_j) at neuron j. We set the leaning coefficient (η) so that the modification in weight, $\Delta W_{ij}(new)$ is not very fast or time consuming. It is generally set above 0 and below 1. The optimal value of η is obtained in the training process (Delurgio 1998).