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Prediction of Agriculture Commodities Price Returns Using ARMA and Wavelet

M. Khalid* Mariam Sultana Faheem Zaidi
Department of Mathematical Sciences, Federal Urdu University, Karachi
* E-mail of corresponding author: khalidsiddiqui@fuuast.edu.pk

Abstract
This Alongside the market participants who calculate the market impact on international events as well as domestic events, price recording has also become crucial for market participants involved in the agricultural policy. Due to large variation in the commodity prices, many around the globe are busy in evaluating the best procedure for its forecasting. This paper demonstrates the techniques that predict the market prices of grains using ARMA and wavelet transformation. A monthly data from July 1983 to July 2013, with 300 observations have been used. After checking the precision of these models with the help of three different error tests, it turns out, that wavelet forecasting method is best for grain market prices.
Keywords: ARMA, Wavelet, Wheat, Rice, Maize, Barley, Error Analysis

1. Introduction

For the last 10 years, huge fluctuations in commodity prices are a serious concern for both the policy makers and the general public. Market fundamentals still carry a significant role in evaluating price levels and, sometimes, variations in price levels can not be explained fully by market fundamentals, especially owing to factors outside the scope of agriculture. The presence of high commodity prices and its volatility raises the question of them being temporary structural changes in agriculture, which are later pondered upon in the economics models.

After the passage of two flourishing seasons of harvests was recorded, the world grain markets in 2010-11 took a crucial turn. First the Russian's export ban, and then the draughts all over the world, caused grain prices to be very high throughout the season. On the other hand, rice prices remained relatively stable.

This study highlights and provides a clear cut analysis of forecasting the grain price. Section 2 reveals literature review, section 3 puts forward data description and methodology, section 4 gives the discussing and results and in section 5, the paper is concluded.

2. Literature Review

Studies of different literatures reveal that grains markets are often analyzed by researchers. Based on the efficient market hypothesis, the futures price is an impartial predictor of the cash price, for a given time period (Fama 1970, 1991). Expert forecast should contain no prognostic information other than that contained in the futuristic market forecast as explained by the efficient market hypothesis. Gardner (1976) proposed to reflect the market's estimate of next period's cash price using a future market price. Rauser & Just (1981) described that forecasts were generally incongruent to the related future market prices.

Garcia, Hudson, and Waller (1988) suggested mixed evidence regarding pricing efficiency of agricultural forecasting models and if they can improve the forecast performance of future. According to Brandt (1985) forecasting by models or individuals can prove to be more accurate as compared to future market, hence packers and producers can benefit from this information. Using vector auto regression Bessler and Brandt (1992) showed that future prices of cattle are inefficient forecasts of actual cash prices. On the other hand, expert forecast and hog futures are almost equal. Irwin, Gerlaw and Liu (1992) when washing over a period of the first quarter of 1980 to the fourth quarter of 1991, agreed that they did not find many significant variations between the US department of agriculture and the forecast accuracy of live cattle futures prices and live hog. Kasten, Jones and Schread (1998) forecasted the five competing commodities i.e. feeder cattle, slaughter steers, cull cows, slaughter hogs, and sows over the period of 1987-96. Zulauf and Irwin (1997) discussed that available data on efficient market is mainly consistent with individual-generated forecasts.

In this research we are optic to predict the prices of grains such as rice, barley, wheat and maize using ARMA and wavelet transformations. The aim of this paper is not to prove that above mentioned methods are best, but it is to show that they are applicable to daily life problems.

3. Data and Research Methodology

The data used in this research is taken from the website of World Bank (http://data.worldbank.org). This monthly data consists of 300 observations starting from July, 1983 to July 2013. It contains international prices of wheat, rice, Barely and Maize.

ARMA is a popular model which is widely adopted for prediction and forecast using the time series data. This model uses no other autonomous variable, prediction is made only using the historical series of a variable. The general ARMA model was introduced by Peter Whittle, and it become common after book by George E. P. Box and Gwilym Jenkins. This model can also express in terms of the lag operator L. The $AR(p)$ model is defined as

$$\varepsilon_t = \left(1 - \sum_{i=1}^{p} \phi_i L^i\right) X_t = \phi(L) X_t \tag{1}$$

where ϕ correspond to the polynomial

$$\phi(L) = 1 - \sum_{i=1}^{p} \phi_i L^i \tag{2}$$

The $MA(q)$ model can be express as

$$X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \varepsilon_t = \theta(L) \varepsilon_t \tag{3}$$

where θ stand for the polynomial

$$\theta(L) = 1 + \sum_{i=1}^{q} \theta_i L^i \tag{4}$$

Lastly, the combined $ARMA(p,q)$ model is defined as

$$\left(1 - \sum_{i=1}^{p} \phi_i L^i\right) X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \varepsilon_t \tag{5}$$

$$\phi(L) X_t = \theta(L) \varepsilon_t \tag{6}$$

Morlet & Giard (1982) presented the idea of a wavelet. Immediately, Alex Grossmann was interested and studied the inverse formula for the wavelet transform; Grossmann and Morlet (1984) derived a detailed mathematical study of the continuous wavelet transforms and their applications; Meyer (1993) yielded the existing literature concerning wavelet. Afterwards, many distinguished mathematicians i.e. A. Grossmann, I. Daubechies, Y. Meyer, S. Mallat, R.A. Devore, Coifmen, V. Wickevhauser made remarkable contributions to the wavelet theory. Here, we only discuss the main concepts of wavelet transformation which have been used later in this paper.

Time-scale wavelets are defined in reference to a mother function $\psi(t)$ of some real variable 't'. The mother function can be individually used to give rise to a whole family of wavelets by translating and scaling the mother wavelet

$$\psi_{(a,b)}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right); \qquad a > 0 \;,\; b \in R \tag{7}$$

Here 'a' is the scaling parameter and 'b' is the translation parameter. The coefficient of this expression can be acquired through the usual projection

$$\psi_{(a,b)} = \int_{-\infty}^{+\infty} f(t) \psi_{(a,b)}(t)\, dt \tag{8}$$

These coefficients gauge the variation of the field $f(t)$ about the point 'b', with the scale given by 'a'. There is an important problem pertaining to selecting the wavelet basis function; since real world data is collected periodically, it is easy to suppose that they are piecewise constant functions and the Haar wavelet would be most appropriate especially for non-stationary signals. In Haar wavelet, like other types of wavelets, a sequence of observation is decomposed into two types of coefficients. The difference coefficients are minute and consist of high-frequency noise, where as the averages coefficients contain much less of noise, as compared to original signal. If original signal X_t have T_o elements, there will be a_1 and d_1 of averages and differences of length $T_1 = \frac{T_o}{2}$. The input for the next level of decomposition is a_1, where for this second iteration, $T_2 = \frac{T_1}{2}$.

The formulae of $a_{j,t}$ and $d_{j,t}$ are as follows:

$$a_{j,t} = \frac{(a_{j-1,t} + a_{j-1,2t-1})}{2} \quad (9)$$

$$d_{j,t} = \frac{(a_{j-1,t} + a_{j-1,2t-1})}{2} \quad (10)$$

where for each level of decomposition $t_1 = 1,2,......,T_{j-1/2}$; $j = 1,2,.....,J$ and $a_o = X_t$. This decomposition can be kept on by decomposing the averages itself to an averages and a differences and so on. This process can be continued indefinitely, but there is a criterion $T_j = 2^j$ to determine an appropriate level of decomposition. After getting the averages and the differences, they are all independently forecasted by any forecasting method. In our calculation, we used ARMA forecasting model.

After decomposing the original signal to the coefficient, the coefficients are converted to a series form such that their summation results in the original signal. This process is undertaken using a method called Inverse Discrete Wavelet Transform, and is called reconstruction. The forecasted values are all then summed up together to get the forecasted values of the original series

4. Discussion of Results

The test statistics used to determine whether the errors from two forecast methods are statistically significant are Mean Absolute Relative Error (MARE), Mean Square of Error (MSE) and Mean Absolute Error (MAE) which are defined by

$$\varepsilon_{MARE} = \frac{1}{N}\sum_{1}^{N}\left|\frac{y_{real} - y_{forecast}}{y_{real}}\right| \quad (11)$$

$$\varepsilon_{MSE} = \frac{\sum_{1}^{N}(y_{real} - y_{forecast})^2}{N} \quad (12)$$

$$\varepsilon_{MAD} = \frac{1}{N}\sum_{1}^{N}\left|y_{real} - y_{forecast}\right| \quad (13)$$

where y_{real} is the real price, $y_{forecast}$ is the forecasted price and N is the number of data points. These errors can be calculated for above mentioned models and comparisons are shown in table 1

5. Conclusion

Commodity prices have long played an important role in accounting for economic fluctuations. Forecasting changes in commodity prices is therefore an important component for forward looking policy-makers. The growing use of future markets has raised the question of how much information these prices incorporate about future movements in spot prices. In this study, ARMA time series and wavelet forecasting techniques are proposed for grain market price forecasting. To verify the effectiveness of proposed approaches, error testing is conducted. Error analysis shows that the wavelet is significantly more effective and practically feasible. Hence, the wavelet forecasting model can be utilized as an opportune implement for grain market price forecasting to further augment forecasting precision.

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Errors	MSE		MAE		MARE	
Methods	**ARMA**	**Wavelet**	**ARMA**	**Wavelet**	**ARMA**	**Wavelet**
Wheat	0.003337	0.001271	0.041701	0.020029	1.649873	1.248043
Maize	0.003208	0.001113	0.041570	0.021683	2.710584	3.255890
Barely	0.004399	0.001721	0.045500	0.025244	2.155619	1.681742
Rice	0.003595	0.001340	0.039947	0.018573	1.244806	0.776945

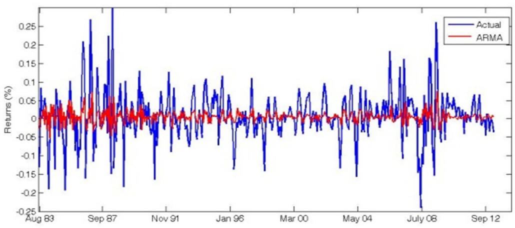

Figure 1a: Shows comparison of original values and forecasted values of Barely by ARMA from 2005-2013

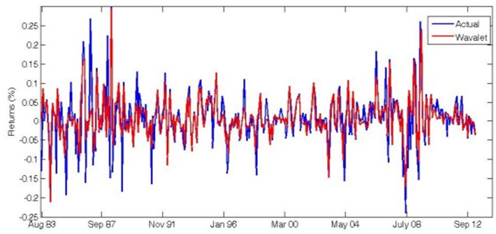

Figure 1b: Shows comparison of original values and forecasted values of Barely by Wavelet from 2005-2013

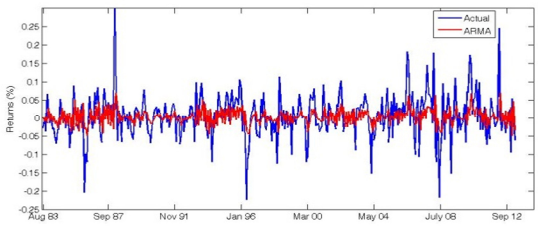

Figure 1c: Shows comparison of original values and forecasted values of Maize by ARMA from 2005-2013

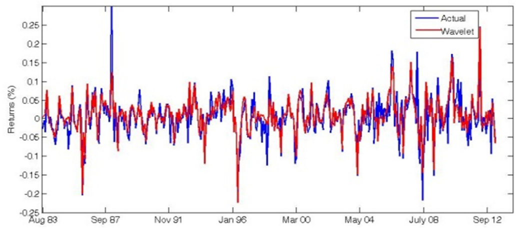

Figure 1d: Shows comparison of original values and forecasted values of Maize by Wavelet from 2005-2013

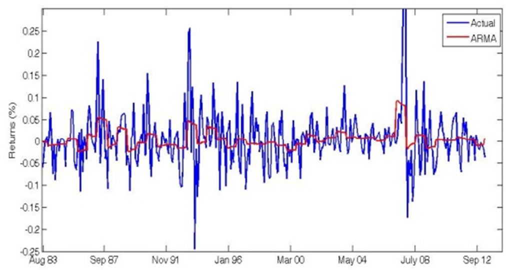

Figure 1e: Shows comparison of original values and forecasted values of Rice by ARMA from 2005-2013

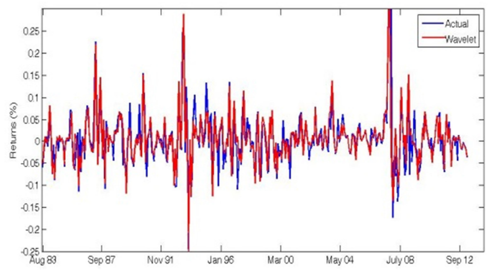

Figure 1f: Shows comparison of original values and forecasted values of Rice by Wavelet from 2005-2013

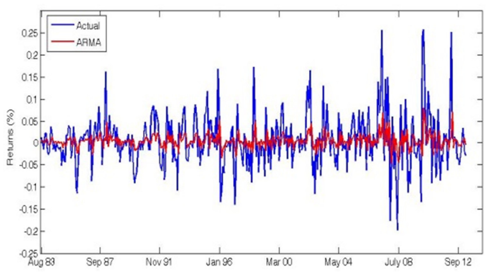

Figure 1g: Shows comparison of original values and forecasted values of Wheat by ARMA from 2005-2013

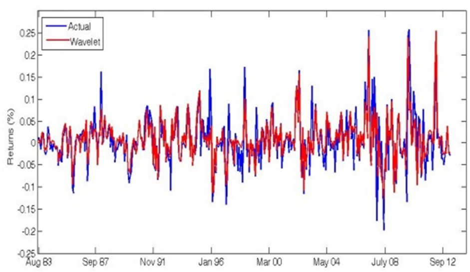

Figure 1b: Shows comparison of original values and forecasted values of Wheat by Wavelet from 2005-2013

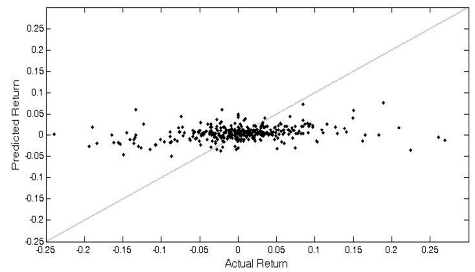

Figure 2a: Shows regression between actual and predicted returns of Barely by ARMA from 2005-2013

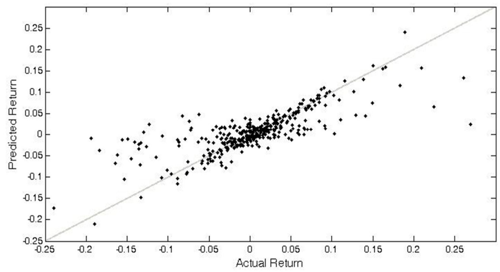

Figure 2b: Shows regression between actual and predicted returns of Barely by Wavelet from 2005-2013

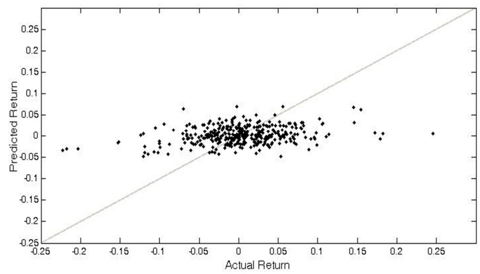

Figure 2c: Shows regression between actual and predicted returns of Maize by ARMA from 2005-2013

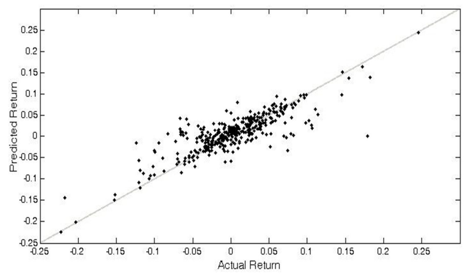

Figure 2d: Shows regression between actual and predicted returns of Maize by Wavelet from 2005-2013

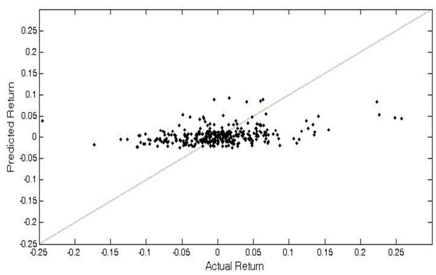

Figure 2e: Shows regression between actual and predicted returns of Rice by ARMA from 2005-2013

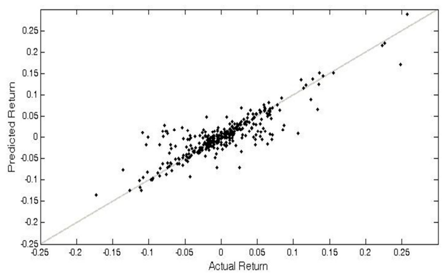

Figure 2f: Shows regression between actual and predicted returns of Rice by Wavelet from 2005-2013

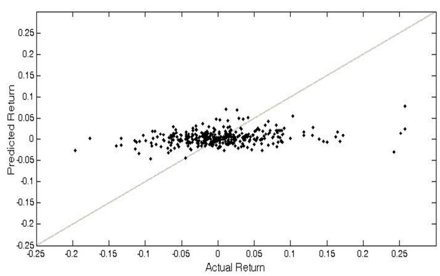

Figure 2g: Shows regression between actual and predicted returns of Wheat by ARMA from 2005-2013

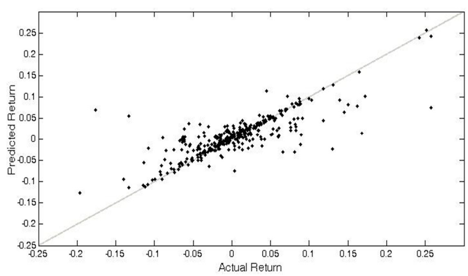

Figure 2d: Shows regression between actual and predicted returns of Wheat by Wavelet from 2005-2013