Forecasting Agriculture Exchange Trade Funds (ETFs): The Application of Grey Relational Analysis (GRA) and Artificial Neural Networks (ANNs)

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INTRODUCTION AND RESEARCH PROBLEM

ETFs and ETNs have become favoured research topics. Since their launch in 1993, ETFs have witnessed spectacular growth, with more than 4,980 ETFs currently being offered to investors. ETNs have shown rapid growth since their launch in 2006 by Barclays Bank PLC. Similar to ETFs, ETNs have many categories, such as commodity ETNs, currency ETNs, emerging market ETNs, and strategy ETNs. An example of commodity ETNs is agricultural ETN. Both agricultural ETFs and ETNs are desired by investors because of their rapid growth. However, despite many studies on ETFs, only a few have examined agricultural ETFs and ETNs. This study aims to fill this research gap and help investors select the best investment by identifying the best model to forecast agricultural ETFs and ETNs. Macroeconomic and financial variables are extracted to examine their effects on agricultural ETFs and ETNs. Several variables, namely, put/call ratio, EUR/USD exchange rate, volatility index (VIX), commodity research bureau index (CRB), short-term trading index (TRIN), New York Stock Exchange composite index (NYA), and weather index (WINX), are utilized. The weather index is added because agricultural products are influenced by weather conditions.

METHODOLOGY

To the best of our knowledge, this paper is the first to forecast agricultural ETFs and ETNs using grey relational analysis (GRA) and two types of the ANN model, namely, back-propagation perception (BPN) and time-delay recurrent neural network (TDRNN). This study also compares and contrasts agricultural ETFs with agricultural ETNs. Jiang and He (2012) also found that the GRA model could accurately compute and predict three real financial time series in China. Bekiros and Georgoutsos (2008) and Sookhanaphibarn et al. (2007) tested the predicting power of the artificial neural network (ANN) model in the financial area. They found that the ANN model has the capacity to offer accurate forecasts in financial areas. Singhal and Swarup (2011) found that electricity price follows a strong trend in deregulated markets.

The localization GRA reflects the association between the reference sequences $x_i^{(0)}(k)$ (is chosen by localization GRG) and the relative sequences $x_i^*(k)$. Hence, the grey relational coefficient $\varepsilon(x_0(k), x_i(k))$ is illustrated as: $\varepsilon(x_0(k), x_i(k)) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{0i}(k) + \zeta\Delta_{max}}$, where $\zeta \in (0,1)$ denotes the notable coefficient.

$$\Delta_{0i}(k) = |x_0(k) - x_i(k)|,$$

$$\Delta_{min} = \min_{\forall i} \min_{\forall k} \Delta_{0i}(k) = \min_{\forall i} \min_{\forall k} |x_0(k) - x_i(k)|, \text{ and}$$

$$\Delta_{min} = \max_{\forall i} \max_{\forall k} \Delta_{0i}(k) = \max_{\forall i} \max_{\forall k} |x_0(k) - x_i(k)|.$$

BPN reduces the differences between the actual network output and the target output. The learning quality from this supervised learning is provided by error function E as follows:

$$E = \frac{1}{2}\sum_{j}(T_j - A_j)^2,$$

where T_j represents the target output of processing element j and A_j indicates the network output of processing element j.

The TDRNN model is an extensive neural model that has both the advantages of adaptive time delays and recurrences. This model manipulates the temporal information of input sequences by utilizing adaptive time delays and recurrent connections. The internal state units serve as the additional inputs at time t and duplicates from the processes of hidden units at time t-1. The TDRNN has adaptable synaptic weights and adjustable time lags through the interconnections between the input and hidden units, while both time delays and weights are also adjusted. The delay box, which is unique on this ANN model, is made up of interconnections from the input layer to the first hidden layer and also from the internal state layer to the first hidden layer.

The net inputs from the activation values of the previous neuron are summed up through the equivalent time delays on each connection line at time t_n of unit j on the layer h that receives a weighted sum.

$$net_{j,h}(t_n) = \sum_{i \in N_{h-1}} \sum_{k=1}^{K_{ji,h-1}} \omega_{jik,h-1} . \alpha_{i,h-1}(t_n - \tau_{jik,h-1}),$$

where $\alpha_{i,h-1}(t_n - \tau_{jik,h-1})$ denotes the activation level of unit i on the layer $h-1$ at time $t_n - \tau_{jik,h-1}$; N_{h-1} represents for the set of nodes of layer $h-1$; and $K_{ji,h-1}$ represent the total number of connection to node j of layer h from node i of layer $h-1$.

RESULTS AND FINDINGS

Agricultural ETNs are strongly influenced by CRB, NYA, WINX, and EUR/USD, whereas agricultural ETFs are strongly influenced by CRB and NYA. Following previous studies, 10%, 20%, 33%, and 50% of the data were utilized to test the available forecasting information applicable to time series data (Andreou et al., 2002; Chen and Fang, 2011; Diaz, 2012). The BPN model suggests that 10% of the time series data must be used to forecast agricultural ETNs and ETFs, whereas the TDRNN model suggests that 33% and 50% of the time series data must be used for the forecasting. GRA and the ANN model can strongly capture nonlinear trends and improve the precision of forecasting the agricultural ETFs and ETNs of Canada, United Kingdom, and the United States. Investors, fund managers, and traders can effectively use CRB, NYA, WINX, and EUR/USD to forecast agricultural ETFs and ETNs.

Consistent with Kim (1998) and Ge et al. (2009), they found that TDRNN can forecast stock market trends and identify and control dynamic systems better than other models. This study presents information on the agricultural ETFs in all variable groups. TDRNN obtained better forecasting results for CORN, COW.TO, and WEAT when 10% of the data were used. Better forecasting results were obtained for DBA when 50% of the data were used. Similarly, better forecasting results were obtained for COTN.L when 33% of the data were used.

CONCLUSIONS, IMPLICATIONS AND SIGNIFICANCE

We find that the CRB and stock indexes strongly influence agricultural ETFs and ETNs. Some agricultural ETNs, such as AGA and ADZ, are strongly influenced by WINX. Coincidentally, the sources of these ETNs are corn, wheat, soybean, and sugar. CRB and NYA can benefit investors, traders, and fund managers when they invest in agricultural ETFs, and CRB, NYA, EUR/US, and WINX can benefit them when they invest in agricultural ETNs. The brief analysis of GRA model strongly suggests that investors should pay more attention to Commodity Index (CRB), New York Stock Exchange Composite Index NYA and weather index (WINX).

The GRA and ANN models can accurately forecast agricultural ETFs and ETNs in the United States, United Kingdom, and Canada as well as support investors, fund managers, and traders in making better predictions. The BPN model reveals that most agricultural ETFs and ETNs can be accurately predicted by using 10% of the time series data. Finally, this study reveals that GRA and ANNs models can accurately forecast agriculture ETFs and ETNs in United States, UK and Canada, and are able to support investors, fund managers and traders to make better-informed prediction.

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