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Procedia Economics and Finance 38 (2016) 106 – 121

Procedia Economics and Finance

www.elsevier.com/locate/procedia

Istanbul Conference of Economics and Finance, ICEF 2015, 22-23 October 2015, Istanbul, Turkey

Markov Switching Artificial Neural Networks for Modelling and Forecasting Volatility: An Application to Gold Market

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Abstract

The study analyses the family of regime switching GARCH neural network models, which allow the generalization of MS type RS-GARCH models to MS-GARCH-NN models by incorporating with neural network architectures. Proposed models differ in terms of both the dynamics of the conditional volatility process and the forecasting capabilities compared to a family of GARCH models. Gray (1996) RS-GARCH model allows regime dependent heteroscedasticity structure following the markov switching methodology of Hamilton (1989). The MS-GARCH-NN model family differ in the sense that, they allow regime switching between GARCH-NN processes. Single regime GARCH-NN models are developed by Donaldson and Kamstra (1996) and further extended by Bildirici and Ersin (2009). Further, the proposed models incorporate a variety of neural network architectures. MS-GARCH-MLP and MS-GARCH-Hybrid-MLP models by Bildirici and Ersin(2014) are augmented with fractional integration (FI) and asymmetric power GARCH variants. And they developed models are MS-FIGARCH-Hybrid-MLP, MS-APGARCH-Hybrid-MLP and MS-FIAPGARCH-Hybrid-MLP models. In this paper, these models were used to test volatility of gold return. Tests are evaluated with MAE, MSE and RMSE criteria and equal forecast accuracy is tested with modified Diebold-Mariano tests. An empirical application is provided for forecasting daily returns in gold market. The results suggest that the proposed approach performs well in modeling and forecasting volatility in daily returns of international gold market.

Peer-review under responsibility of the Organizing Committee of ICEF 2015.

Keywords: Volatility, Gold, Neural Networks, Markov Switching- GARCH , MS-FIGARCH-Hybrid-MLP, MS-APGARCH-Hybrid-MLP, MS-FIAPGARCH- Hybrid-MLP

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Peer-review under responsibility of the Organizing Committee of ICEF 2015.
doi:10.1016/S2212-5671(16)30183-6

1. Introduction

Some papers analyzed the volatility of price of gold. If the results obtained by the papers, which examined the relationship between oil and gold price in the literature, are investigated, it is observed that different results are obtained.

Pindyck and Rotemberg(1990) tested and confirmed the claim that the prices of raw commodities have a persistent tendency to move together. Melvin and Sultan (1990) searched the relation between oil and gold and they determined a strong positive correlation between oil and gold through the export revenue channel. Cashin et al.(1999) analyzed the correlations between seven commodities and they found that there exist significant correlation between oil and gold. Nakamura and Small(2007) determined that both daily gold price and oil price had essentially random walk, and their first differences were independently distributed random variables or time-varying random variables(Zhang and Wei:2010). Sari etal.(2007), examined the relation between commodity prices such as oil, gold, silver and copper and two financial variables such as exchange rate and interest rate. They determined that both gold and exchange rate can explain some of the movements in oil price. Beahm(2008) determined that relationship between oil price and gold price was one of the fundamentals that drive the prices of precious metals. Hammoudeh et al. (2008) pointed out that the price of gold was the forcing variable of the oil price. Liao and Chen (2008) analyzed the relationship between oil prices and gold prices in Taiwan by using TGARCH model and they found that fluctuations of return of oil price influence the returns of gold prices. Ewing et al.(2012) and Fattouh(2010a and b) examined the asymmetry in the adjustment process for oil and metal commodities.

Chiu et al. (2009) showed that there is a unidirectional causality running from WTI oil to gold (Le and Chang: 2011). Narayan et al.(2010) found co-integration relationship between spot prices of gold-oil and future prices of gold-oil. Zhang and Wei (2010) found out a consistent trend between crude oil and gold price during period of January 2000 and March 2008. Oil price linearly Granger causes the volatility of gold price but changes in gold price do not linearly cause oil price volatility. Wang et al. (2011) found bi-directional causal relationship between oil price and gold price. Hsiao et.al. (2013) tested the correlation among oil prices, gold prices and exchange rates over the period between 09.2007 and 12.2011.

Some papers used to non-li,near models to analyse the relation between variables. For example, Bildirici and Turkmen(2015) aims to analyze the cointegration and causality relationship among oil and precious metals of gold, silver and copper by using nonlinear ARDL and two popular nonlinear causality tests; Mackey Glass and non-linear casualty, for the period from 1973:1 through 2012:11 monthly. Some other papers used GARCH models.

Ewing and Malik (2012) employed univariate and bivariate GARCH models to examine the volatility of gold and oil incorporating structural breaks. They found strong evidence of significant transmission of volatility between returns of gold and oil when structural breaks in variance are accounted for in the model. Some of these studies explained the relationship between gold and oil prices through the inflation channel. Gencer and Kılıç(2014) tested the impact of oil and gold returns and their volatilities via multivariate CCC M-GARCH model. They analysed 28 different portfolio investments consisting equal investments in oil, gold and each sector index by turn and determined that oil GARCH effects are significant and close to unity in each model. According to their's results, Gold GARCH effects follow oil GARCH parameters in magnitude, implying that gold prices also have significant effects on portfolio volatility. Tiwari and Sahadudheen (2015), explored the relationship between real oil price and real gold price over a period of 1990 April to 2013 August. In order to check for the impact of real oil price on the real gold, return on real oil and return on real gold are used. The study employed types of GARCH models which suggested that an increase in real oil price has positive effects on gold. The EGARCH model provides the evidence that a 10% increase in the oil price returns leads to 4.7% increase of gold and shocks to gold price have an asymmetric effect, which means positive and negative shocks have different effect on gold price in terms of magnitude.

This study can be defined as complementary of the previous empirical papers. This paper is aim to investigate the volatility of return of gold price in Turkey. Since Turkey is the fourth largest gold-consuming country. Gold is containing all the roles as a store of value and means of exchange. Gold is seen as a safe haven, especially in times of crisis. Gold exhibit important price volatility, the long-term price trend is important in reinforcing its safe-haven property. Gold remains as a safe haven in the long term, though short-term price fluctuations exist. Gold prices produce substantial implications for the movement of macroeconomic and financial variables. We used non-linear method as Markov Switching- ARMA-GARCH method developed by Bildirici and Ersin(2014).

This paper is structured as follows. In the second section of this paper, Markov Switching ARMA GARCH Models are given. Section 3 presents data and econometric methodology. In section 4, empirical results are presented. Final section includes conclusions and policy implications.

2. Models

Markov Switching model has interesting properties to be examined such as the stationarity and switching course of volatility observed within the asset prices. Kanas and Yannopoulos (2001) and Kanas (2003), Bildirici and Ersin(2014) used Markov Switching and Neural Networks techniques for forecasting stock returns, however their applications depart from the approach followed in this study.

The study aims at integrating MS and ANN modeling techniques. Accordingly, traditional ARMA-GARCH model is further augmented with ANN and MS structures. The approach aims formulations and estimations of MS-ARMA-GARCH-MLP (MS-ARMA-APGARCH-MLP, MS-ARMA-FIGARCH-MLP, MS-ARMA-FIAPGARCH-MLP).

2.1. Markov Switching ARMA GARCH Models

We used non-linear method as Markov Switching- ARMA-GARCH method developed by Bildirici and Ersin(2014)

The MS-ARMA-GARCH-MLP model is defined of the form,

$$y_t = c_{(s_t)} + \sum_{i=1}^{r} \theta_{i,(s_t)} y_{t-i} + \varepsilon_{t,(s_t)} + \sum_{j=1}^{n} \varphi_{j,(s_t)} \varepsilon_{t-j,(s_t)} \tag{1}$$

$$\sigma^2_{t,(s_t)} = w_{(s_t)} + \sum_{j=1}^{p} \alpha_{j,(s_t)} \varepsilon^2_{t-j,(s_t)} + \sum_{k=1}^{q} \beta_{k,(s_t)} \sigma_{t-k,(s_t)} + \sum_{h=1}^{m} \xi_{h,(s_t)} \psi\left(z_t \lambda_h\right) \tag{2}$$

where, i=1,…,m are the regimes, which are governed by unobservable Markov process,

$$\sum_{i=1}^{m} \sigma^2{}_{t(i)} P\left(S_t = i \middle| z_{t-1}\right) \tag{3}$$

$$\psi\left(z_t \lambda_h\right) = \left[1 + \exp\left(\lambda_{h,d,w} + \sum_{d=1}^{1} \left[\sum_{w=1}^{m} \lambda_{h,d,w} z^{w}_{t-d}\right]\right)\right]^{-1} \tag{4}$$

$$\left(1/2\right)\lambda_{h,d,w} \sim uniform\ \left[-1,+1\right] \tag{5}$$

and $P\left(S_t = i \middle| z_{t-1}\right)$, the filtered probability with the following representation,

$$\left(P\left(S_t = i \middle| z_{t-1}\right)\alpha f\left(P\left(\sigma_{t-1} \middle| z_{t-1}, s_{t-1} = 1\right)\right)\right) \tag{6}$$

If $n_{j,i}$ transition probability $P\left(s_t = i \middle| s_{t-1} = j\right)$ is accepted,

$$z_{t-d} = \left[\varepsilon_{t-d} - E(\varepsilon)\right] \Big/ \sqrt{E\left(\varepsilon^2\right)} \tag{7}$$

$s \to \max\{p,q\}$ recursive procedure is started by constructing $P\left(z_s = i \middle| z_{s-1}\right)$, where $\psi\left(z_t \lambda_h\right)$ is considered as logistic activation function of the form 1/(1+exp(-*x*)). The weight vector $\xi = w$; ψ =*g* logistic activation function and input variables are defined as $z_t \lambda_h = x_i$ where λ_h is defined as in Eq. (5).

If $n_{j,i}$ transition probability $P\left(z_t = i \middle| z_{t-1} = j\right)$ is accepted,

$$f\left(y_t \middle| x_t, z_t = i\right) = \frac{1}{\sqrt{2\pi h_{t(i)}}} \exp\left\{ -\left(y_t - x_t'\varphi - \sum_{j=1}^{H} \beta_j p\left(x_t'\gamma_j\right)\right)^2 \Big/ 2h_{t(j)} \right\} \tag{8}$$

$s \to \max\{p,q\}$ recursive procedure is started by constructing $P\left(z_s = i \middle| z_{s-1}\right)$.

The model given in equation (2) is modified to obtain the Markov Switching APGARCH (MS-ARMA-APGARCH-MLP) model,

$$\sigma_{t,(s_t)}^{\delta,(s_t)} = \alpha_{(s_t)} + \sum_{k=1}^{r} \varphi_{k,(s_t)} \left(\left|\varepsilon_{t-k}\right| - \gamma_k \varepsilon_{t-k} \right)^{\delta,(s_t)} + \sum_{j=1}^{q} \beta_{j,(s_t)} \sigma_{t-j,(s_t)}^{\delta,(s_t)} + \sum_{h=1}^{s} \xi_{h,(s_t)} \psi\left(z_t \lambda_h\right) \tag{9}$$

where, *t*=1,…,*m* regime model and regimes are governed by unobservable Markov process. Equations (3) through (9) define the MS-ARMA-APGARCH-MLP model modified with the ANN and the logistic activation function $\psi\left(z_t \lambda_h\right)$. Note that the MS-ARMA-APGARCH-MLP model reduces to the MS-ARMA-GARCH-MLP model if the power term δ =2 and γ_k =0. Similarly, the model reduces to the MS-ARMA-GARCH-MLP model for γ_k =0, and to the MSGJRGARCH-MLP model if δ =2 and $0 \le \gamma_k \le 1$ are imposed. The model may be shown as MSTGARCH-MLP model if δ =1 and $0 \le \gamma_k \le 1$. Similarly, with *t*=1 so that $s_t = s = 1$, the quoted models reduce to single regime versions; MS-ARMA-APGARCH-MLP, MS-ARMA-GARCH-MLP, MSNGARCH-MLP, MSGJRGARCH-MLP and MS-ARMA-GARCH-MLP models (For further discussion in NN-GARCH family models, see Bildirici and Ersin, 2009. For a traditional representations of single regime GARCH models readers may refer to Bollersev, 2007).

MS-ARMA-FIAPGARCH model is augmented with neural network modeling architecture to obtain MS-ARMA-FIAPGARCH-MLP. For augmentation of different GARCH specifications with neural networks, see: Bildirici and Ersin (2009). The conditional variance is defined as,

$$\left(1-\beta_{(s_t)}L\right)\sigma_{n,(s_t)}^{\delta_{(s_t)}} = \omega_{s_t} + \left(\left(1-\beta_{(s_t)}L\right) - \left(1-\phi_{(s_t)}L\right)\left(1-L\right)^{d_{(s_t)}}\right)\left(\left|\varepsilon_{n-1,s_t}\right| - \gamma_{k,(s_t)}\varepsilon_{n-1,s_t}\right)^{\delta_{(s_t)}} + \sum_{h=1}^{s} \xi_{h,(s_t)} \psi\left(z_t \lambda_h\right) \tag{10}$$

where, h are neurons defined with sigmoid type logistic functions, t=1,…,m regime states governed by unobservable variable following Markov process. Equation (10) defines the MS-ARMA-FIAPGARCH-MLP model, the fractionally integration variant of the MSAGARCH-MLP model modified with the ANN and the logistic activation function $\psi(z_t\lambda_h)$. Similarly, the MS-ARMA-FIAPGARCH-MLP model reduces to the MSFIGARCH-MLP model for restrictions on the power term $\delta_{(s_t)}$=2 and $\gamma_{k,(s_t)}$=0; the model reduces to MSFINGARCH-MLP model for $\gamma_{k,(s_t)}$=0; and to the MSFIGJRGARCH-MLP model if $\delta_{(s_t)}$=2 and $\gamma_{k,(s_t)}$ is so that it varies between $0 \le \gamma_{k,(s_t)} \le 1$. Further, the model may be shown as MSTGARCH-MLP model if $\delta_{(s_t)}$ =1 in addition to the $0 \le \gamma_{k,(s_t)} \le 1$ restriction. On the contrary, if single regime restriction t=1 is imposed, models discussed above; namely, MS-ARMA-FIAPGARCH-MLP, MSFIGARCH-NN, MSFIGARCH-NN, MSFINGARCH-MLP, MSFIGJRGARCH-MLP and MSFITGARCH-MLP models reduce to NN-FIAPGARCH, NN- FIGARCH, NN-FIGARCH, NN-FINGARCH, NN-FIGJRGARCH and NN-FITGARCH models, which are single regime variants that do not possess Markov switching type asymmetry (For further discussion in NN-GARCH family models, see Bildirici and Ersin, 2009. For traditional representations of single regime GARCH models readers may refer to Bollersev, 2007).

Furthermore, the model could be represented with short memory characteristics under restrictions on fractional integration parameters. By imposing $d_{(s_t)} = 0$ to the fractinal differentiation parameter which may take different values under i=1,2,…,m different regimes, the model in Eq. (10) reduces to MS-ARMA-APGARCH-MLP model, the short memory model variant. In addition to the restrictions applied above, application of $d_{(s_t)} = 0$ results in models without long memory characteristics: MS-ARMA-FIAPGARCH-MLP, MS-ARMA-GARCH-MLP, MS-ARMA-GARCH-MLP, MSNGARCH-MLP, MSGJRGARCH-MLP and MSTGARCH-MLP models.

For a typical example, consider a MS-ARMA-FIAPGARCH-MLP model representation with two regimes,

$$\begin{aligned}
\left(1-\beta_{(1)}L\right)\sigma_{n,(1)}^{\delta_{(1)}} &= \omega+\left(\left(1-\beta_{(1)}L\right)-\left(1-\phi_{(1)}L\right)\left(1-L\right)^{d_{(1)}}\right)\left(\left|\varepsilon_{n-1}\right|-\gamma_{k,(1)}\varepsilon_{n-1}\right)^{\delta_{(1)}}+\sum_{h=1}^{s}\xi_{h,(1)}\psi\left(z_t\lambda_h\right)\\
\left(1-\beta_{(2)}L\right)\sigma_{n,(2)}^{\delta_{(2)}} &= \omega+\left(\left(1-\beta_{(2)}L\right)-\left(1-\phi_{(2)}L\right)\left(1-L\right)^{d_{(2)}}\right)\left(\left|\varepsilon_{n-1}\right|-\gamma_{k,(2)}\varepsilon_{n-1}\right)^{\delta_{(2)}}+\sum_{h=1}^{s}\xi_{h,(2)}\psi\left(z_t\lambda_h\right)
\end{aligned} \tag{11}$$

Following the division of regression space into two regimes with Markov switching, the model allows two different asymmetric power terms $\delta,(1)$ and $\delta,(2)$ and two different fractional differentiation parameters; as a result, different long memory and asymmetric power structure are allowed in two distinguished regimes.

It is possible to show the model, as a single regime NN-FIAPGARCH model if t=1,

$$\left(1-\beta L\right)\sigma_n^{\delta} = \omega+\left(\left(1-\beta L\right)-\left(1-\phi L\right)\left(1-L\right)^{d}\right)\left(\left|\varepsilon_{n-1}\right|-\gamma_k\varepsilon_{n-1}\right)^{\delta}+\sum_{h=1}^{s}\xi_h\psi\left(z_t\lambda_h\right) \tag{12}$$

and further, the model reduces to Bildirici and Ersin (2009) NN-FIGARCH if t=1 and $\delta_{(s_1)} = \delta$ =2,

$$\left(1-\beta L\right)\sigma_n^{2} = \omega+\left(\left(1-\beta L\right)-\left(1-\phi L\right)\left(1-L\right)^{d}\right)\left(\left|\varepsilon_{n-1}\right|-\gamma_k\varepsilon_{n-1}\right)^{2}+\sum_{h=1}^{s}\xi_h\psi\left(z_t\lambda_h\right).$$

3. Data and Econometric Results

3.1. The Data

In order to test forecasting performance of the above-mentioned models, gold return in Turkey is calculated by using the daily closing prices of Istanbul Gold Stock Index IGSE 100 covering the 27.07.1995-31.01.2013 period. To obtain return series, the data is calculated as follows: y=ln(Pt/Pt-1) where ln(.) is the natural logarithm and taken as a measure of stock returns. In the process of training the models, the sample is divided between training, test and out-of-sample samples with the percentages of 80%, 10%, 10%.

3.2. Econometric Results

In Table 2, transition matrix and the MS model were estimated. The standard deviation takes the values of 0.05287 and 0.014572 for regime 1 and regime 2. It lasts approximately 75.87 months in regime 1 and 107.61 months in regime 2. By using maximum likelihood approach, MS-GARCH models are tested by assuming that the error terms follow student-t distribution with the help of BFGS algorithm. Number of regimes is taken as 2 and 3. GARCH effect in the residuals is tested and at 1% significance level, the hypothesis that there are no GARCH effects is rejected. Additionally, the normality in the residuals are tested with Jarque-Berra test, at 1% significance level, it is detected that the residuals are not normally distributed. As a result, MS-GARCH model is estimated under the t distribution assumption. In the MS-GARCH model, the transition probability results are calculated as Prob(st=1|st−1=1)= 0.50 and Prob(st = 2|st−1=2)=0.51 and show that the persistence is low in the MS-GARCH model.

To escape local optima, the log-likelihood functions were maximized with simulated annealing (Goffc el al, 1994). Statistical inference regarding the emprical validity of two-regime switching process was carried out by using nonstandart LR tests (Davies: 1987). The non-standart LR test is statistically significant and this suggests that linearity is strongly rejected.

On the other hand, though the improvement by shifting to modeling the conditional volatility with regime switching is noteworthy, the desired results are still not obtained, therefore, MS-GARCH models are extended with MLP, RBF and RNN models and their modeling performances are tested.

1. MS- GARCH

	arch	*garch*	*sigma*	*constant*	$p_{0\mid 0}$	$P_{1\mid 1}$	*LogL*	*RMSE*
	0.03351	0.966483	0.000333727	6.23008e-005	0.500244	0.5102	385.09	0.458911
Regime 1.	(0.005)***	(0.01307)***	(1.916e-006)***	(1.360e-005)***				
	0.56387	0.436124	0.0004356	6.29344e-005				
Regime 2.	(0.0098)***	(0.01307)***	(1.231e-005) ***	(1.161e-005)***				

2.. MS-APGARCH

	arch	*garch*	*sigma*	*constant*	*mean*	$P_{0\mid 0}$	$p_{1\mid 1}$	*POWER*	*LogL*	*RMSE*
	0.383241	0.616759	0.000679791	8.13394e-005				0.80456		
Regime 1.	(0.0102)***	(0.01307)***	(5.685e-006)***	(2.007e-005)***	0.00021042	0.500227	0.50300	(0.00546)***	1756.5	0.42111
	0.20805	0.791950	0.0012381	8.20782e-005				0.60567		
Regime 2.	(0.0201)***	(0.01307)***	(3.451e-004)***	(1.835e-005)***	2.83E-03			(0.0234)***		

3. MS-FIAPGARCH

	arch	*garch*	*d-figarch*	*aparch(gamma1)*	*aparch (delta)*	*constant*	$p_{0\mid 0}$	$p_{0\mid 1}$	*LogL*	*RMSE*
	0.277721	0.67848	0.2761233	0.220157	0.123656	0.00135				
Regime 1.	(0.00)***	(0.00)***	(0.0266)***	(0.0106)***	(0.001)***	(0.001)	0.50212	0.510021	1877.9	0.42220
	0.309385	0.680615	0.181542	0.21083	0.1448	0.00112				
Regime 2.	(0.002)***	(0.0001)***	(0.00005)***	(0.0299)***	(0.0234)***	(0.00984)				

3.2.1. MS-GARCH-NN Results

In the study, model estimation is gathered through utilizing backpropagation algorithm and the parameters are updated with respect to a quadratic loss function; whereas, the weights are iteratively calculated with weight decay method to achieve the lowest error. Alternative methods include Genetic Algorithms (Goldberg, 1989) and 2nd order derivative based optimization algorithms such as Conjugate Gradient Descent, Quasi-Newton, Quick Propagation, Delta-Bar-Delta and Levenberg-Marquandt, which are fast and effective algorithms but may be subject to over-fitting (see Patterson, 1996; Haykin, 1994; Fausett, 1994). In the study, we followed a two-step methodology. Firstly, all models were trained over a given training sample vis-à-vis checking for generalization accuracy in light of RMSE criteria in test sample. The approach is repeated for estimating each model for 100 times with different number of sigmoid activation functions in the hidden layer. Hence, to obtain parsimonic models, best model is further selected with respect to the AIC information criterion (see Faraway and Chatfield, 1998). For estimating NN-GARCH models with early stopping combined with Algorithm Corporation, readers are referred to Bildirici and Ersin (2009). The estimated models are reported in Table 4 in which the MSE and RMSE values for training samples are given for comparative purposes.

Table 4. Markov Switching GARCH Neural Network Models: Training Sample Results

Model Group 1: MS-GARCH-Neural Network Models		
	MSE	***RMSE***
MS-GARCH-MLP	0.034665716	0.186187315
MS-APGARCH-MLP	0.02659193463905	0.16307033647800
MS-FIGARCH-MLP		
MS-FIAPGARCH-MLP	0.03122180375144	0.17669692626482

MS-APGARCH-NN family models, models with asymmetric power terms are reported in the second section of Table 4.

MS-FIAPGARCH-NN family models, models augmented fractional integration are are reported in the third section of Table 4.

Table 5. Regime Switching GARCH Neural Network Models: Test Sample Results

Model Group 1: MS-GARCH-Neural Network Models		
	MSE	***RMSE***
MS-GARCH-MLP	0.015333378	0.123828017
MS-APGARCH-MLP	0.00000001333791	0.00011548986313
MS-FIGARCH-MLP		
MS-FIAPGARCH-MLP	0.00000001389543	0.00011787886146

It is noted that, as we move from MS-GARCH-NN models towards MS-APGARCH-NN and fractionally integrated models of MS-FIAPGARCH-NN; the gains from hybrid modeling of MS, GARCH and ANN models are noteworthy. One point that cannot be overlooked is the fact that, in addition to the improvement in terms of the training sample, the results which are to be evaluated for the test sample and most importantly, for the out-of-sample forecasts deserve special attention. The results obtained for the test sample are reported in Table 5.

Among the first group of models, Model Group 1, MS-GARCH-MLP model takes the 1st place with RMSE=0.1238. The second group is the MS-APGARCH-NN models. In this group, MS-APGARCH-Hybrid MLP model has the lowest RMSE with 0.00011539. The forecast capability increases sharply by moving from the GARCH based models to the APGARCH based markov switching neural network models.

The third group, MS-FIAPGARCH-NN models are given in the last section of Table 5. Compared to the Model Group 1 (MS-GARCH-NN), Model Group 3 shows sharp improvement in terms of generalization in the test sample. Overall, Group 2 has the best performance, though the performance of Group 3 is very promising.

Forecast Results

In Table 6, the models are compared in terms of the out-of-sample forecast performances. For comparative purposes, the RMSE and MSE error criteria are also reported for MS-GARCH, MS-APGARCH and MS-FIAPGARCH models taken as the baseline models in comparative analysis. Among the models in Group 1, MS-GARCH-MLP has the lowest RMSE (=0.1238). Considering the RMSE=0.4589 obtained for MS-GARCH model, models with neural network architectures provide significant improvement over the regime switching GARCH model in terms of forecasting.

Table 6. Markov Switching GARCH Neural Network Models: Out of Sample Results

Model Group 1: MS-GARCH-Neural Network Models		
	MSE	***RMSE***
MS-GARCH	0.210599	0.458911 (2nd)
MS-GARCH-MLP	0.015333378	0.123828017 (1st)
Model Group 2: MS-APGARCH-Neural Network Models		
MS-APGARCH	0.1774	0.421110 (2nd)
MS-APGARCH-MLP	0.00000001333791	0.00011548986313 (1st)
Model Group 3: MS-FIAPGARCH-Neural Network Models		
MS-FIAPGARCH	0.17814	0.4222066 (2nd)
MS-FIAPGARCH-MLP	0.00000001389543	0.00011787886146 (1st)

In Model Group 2, MS-APGARCH- MLP model is the 1st model with the lowest RMSE in forecasting (RMSE=0.00011548986313). The 1st model is followed by the MS-FIAPGARCH-MLP (RMSE=0.00011787886146) and MS-GARCH-MLP (RMSE=0.123828017) deserving the 2nd and 3rd places.

Thus, the neural network augmented versions show significant improvement in forecasting.

Diebold-Mariano equal forecast accuracy tests will be applied to evaluate the models. Results are given in Table 7. The forecasting sample corresponds to the last 587 observations of ISE100 daily returns. [r] denotes that the “row model” is selected over the “column model”. Similarly, [c] shows that the selected model is the column model with respect to the Diebold-Mariano test.

In Group 1, the null hypothesis of equal forecast accuracy is rejected in favor of the MS-GARCH-Hybrid MLP over the MS-GARCH-RBF. Further, MS-GARCH-MLP is also selected over MS-GARCH-RBF. The equal forecast accuracy hypothesis is rejected at 1% significance level for MS-GARCH-Hybrid MLP and MS-GARCH-MLP and the test suggested that the MS-GARCH-MLP provided forecast accuracy improvement over MS-GARCH-Hybrid MLP. Hence, MS-GARCH-MLP model is selected as the model with highest forecast accuracy in Model Group 1. Baseline MS-GARCH model is the last model similar to the results obtained in Table 6.

The asymmetric power GARCH architecture based models in Group 2 are evaluated at the second part of Table 7. Similar to the results obtained for the RBF based model in the first section of the table, the null hypotheses of equal forecast accuracy are rejected and the DM tests favored MS-APGARCH-Hybrid MLP and MS-APGARCH-MLP models over the MS-APGARCH-RBF model at 1 % significance level.

Table 7. Diebold Mariano Equal Forecast Accuracy Test Results, Out of Sample

Model Group 1: MS-GARCH-Neural Network Models		
	MS-GARCH	***MS-GARCH-MLP***
MS-GARCH	-	27.13*** (0.000)[c]
MS-GARCH-MLP	-	-
Model Group 2: MS-APGARCH-Neural Network Models		
		MS-APGARCH-MLP
MS-APGARCH	-	56.42*** (0.000)[c]
MS-APGARCH-MLP	-	-
Model Group 3: MS-FIAPGARCH-Neural Network Models		
	MS-FIAPGARCH	***MS-FIAPGARCH-MLP***
MS-FIAPGARCH	-	56.61*** (0.000)[c]
MS-FIAPGARCH-MLP	-	-

Diebold-Mariano (1995) test statistics are reported. ***, **, * denotes significance at 1%, 5% and 10%. Selected model is given in [ ] where *c* denotes the column model, *r* denotes the row model. DM tests are calculated by using the MAE criteria and maximum lag length is selected with Bartlett kernel

Diebold-Mariano test results for the models with fractional integration are reported in the last section of Table 7. The null hypothesis of equal forecast accuracy among MS-FIAPGARCH-MLP and MS-FIAPGARCH is also rejected and the test favored the MS-FIAPGARCH-MLP model. Further, if MS-FIAPGARCH-MLP and MS-FIAPGARCH-Hybrid MLP models are compared, DM test suggests that though the MSE is lower for MS-FIAPGARCH-Hybrid MLP model, the null hypothesis of equal forecast accuracy cannot be rejected. If an overlook is to be provided, all NN augmented MS-FIAPGARCH based models provided significant gains in terms of forecast accuracy compared to the baseline MS-FIAPGARCH model.

Conclusions

In the study, a family of regime switching neural network augmented volatility models are discussed and analyzed and an application to daily returns in an emerging market stock index is presented. In this respect, the GARCH-NN neural network model family is generalized to MS type regime switching. The suggested models are MS-GARCH-NN models incorporated with neural network architectures based on MLP, RBF and Hybrid MLP. Following Gray (1996) RS-GARCH model which allows for within regime heteroskedasticity with markov switching of Hamilton (1989), the models analyzed in the study allow regime switching modeled with GARCH-NN model in the spirit of Donaldson and Kamstra (1996) and further generalized to a family of GARCH-NN models by Bildirici and Ersin (2009). The model analyzed are MS-GARCH-MLP which are further extended to account for asymmetric power terms based on the APGARCH architecture; MS-APGARCH-MLP and lastly extended to fractional integration by MS-APGARCH-MLP.

Models are evaluated with MSE and RMSE error criteria and Diebold Mariano tests for possible improvements in terms of forecasting. It is observed that, holding the gains in the training sample on one side, the real improvement occurs for the test sample and most importantly in the out-of-sample forecasting. By evaluating MS-GARCH-NN models, though in-sample performance is noticeable, moving towards MS-APGARCH-NN models and fractionally integrated models of MS-FIAPGARCH-NN show significant improvement in light of the MSE and RMSE criteria and in terms of Diebold-Mariano equal forecast accuracy tests.

Specially, gold is used in various sectors and is viewed as the most influential metal due to its functions; such as storage of value, reserve for money, safe haven property as an anti-inflation shelter and financial investment instrument.

The price movements in gold can have an impact on changing the price trends of the whole economy. In this way, investigating their relationship over price discovery helps to provide some information for both the gold price and the potential effects on commodity markets.

Strong policy measures need to be adopted to ensure that gold price returns to its original trend.

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