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Applications of Neural Networks in modeling and forecasting volatility of crude oil markets: Evidences from US and China

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Abstract. Previous researches on oil price volatility have been done with parametric models of GARCH types. In this work, we model volatility of crude oil price based on GARCH(p,q) by using Neural Network which is one of powerful classes of nonparametric models. The empirical analysis based on crude oil prices in US and China show that the proposed models significantly generate improved forecasting accuracy than the parametric model of normal GARCH(p,q). Among nine different combinations of hybrid models (for p = 1,2,3 and q = 1,2,3), it is found that NN-GARCH(1,1) and NN-GARCH(2,2) perform better than the others in US market whereas, NN-GARCH(1,1) and NN-GARCH(3,1) outperform in Chinese case.

Introduction

Oil price volatility. Crude oil plays a crucial role in the world economy as it causes significant impact on key macroeconomic indicators [1]. Over 30 years, oil has become the biggest traded commodity in the world. Recently oil price volatility has caused great concern among consumers, corporations and governments. Oil price volatility is an important measure used in derivative option pricing, portfolio section and risk management. Therefore, huge numbers of researches have been done on modeling and forecasting volatility of oil prices. GARCH models of Engle and Bollerslev [2,3] are the inspiration of modeling the oil price volatility; and then its extensions are also applied [4-8]. However, these works focused only on parametric model based approaches, and oil price volatility based on nonparametric approach, Neural Networks, has not been done yet.

Neural Networks in Volatility modeling. Neural Network, (NN) is a class of generalized nonlinear nonparametric models inspired by studies of the brain and nerve system. Recently, it has been widely used in various fields of researches including regression and time series prediction. See [9] for its literature, scientific applications and its uses in finance. The main appealing of using the NN over more conventional econometric models is that the NN is best of approximating any (nonlinear) functions without prior assumptions on the underlying data generating process, [10]. Furthermore, the NN model overcomes the limitations faced by the traditional prediction models such as normality assumption on estimation, linearity, biased outliers and misspecification. Therefore, the NN have been successfully applied in financial volatility models [11-13].

Inspired by such successfully predictive performance of this Neural Network, in this work, we propose to model crude oil price volatility based on GARCH(p,q) by using the neural network, denoted as NN-GARCH(p,q) in short. Previous literature focused only on the case of NN-GARCH with (p=1 and q=1) and tested with stock market and exchange rate volatilities only; but here we go further for p=1,2,3 and q=1,2,3 cases and test with oil price volatility. We use two markets of oil prices, US and China, to assess and validate our proposed models. This paper is organized as follow. Next section describes experimental design including data description and NN-GARCH(p,q) modeling. In section 3, we illustrate the experimental results. The last section concludes our work.

Methodology and Experimental Design

Let P_t be crude oil price at time t. We use square of y_t defined below to be the actual volatility of oil price, $y_t = 100.(\ln P_t - \ln P_{t-1})$. Then, GARCH(p,q) is defined as

$$y_t = \mu_t + \varepsilon_t \,,\ \varepsilon_t/I_t \sim N(0,\ \sigma_t^2)\,, \sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \quad (1)$$

where $\omega > 0, \alpha_i \geq 0, \beta_j \geq 0$; I_t represents the information sets available at time t.
Our proposed GARCH(p,q) model can be modified as

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i g_{t-i}(\varepsilon_{t-i}^2) + \sum_{j=1}^{q} \beta_j h_{t-j}(\sigma_{t-j}^2) \quad (2)$$

where unknown functions $g_i(.)$ and $h_j(.)$ represent nonlinear relations and they are approximated by Neural Network learning algorithm.

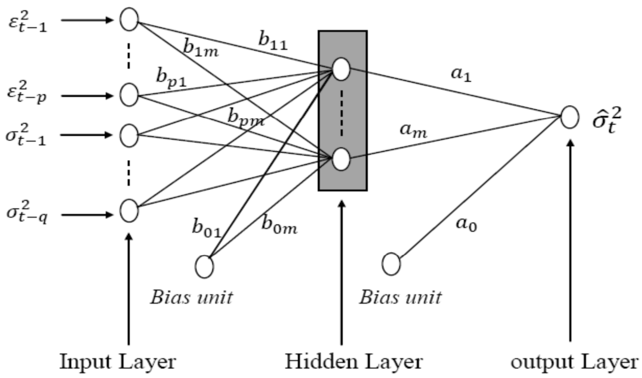

Fig.1 Architecture of Feed-forward Neural Network in this work.

Data sets. In this experiment, we examine two data sets of oil prices in US and China to validate our proposed models. The first data is Weekly United States Spot Price FOB Weighted by Estimated Import Volume (and it is in Dollars per Barrel). The second dataset is Weekly China Daqing Spot Price FOB (converted in Dollars per Barrel). Both oil prices are collected from US Energy Information Administration(EIA) website and is transformed into log rate of change. Fig.2 plot two time series of oil price volatility for both US (left) and Chinese markets (Right). From these plots, we can see that US oil price is more volatile than oil price in China. It is obviously true that the global financial crisis did not cause Chinese oil price so volatile like in US.

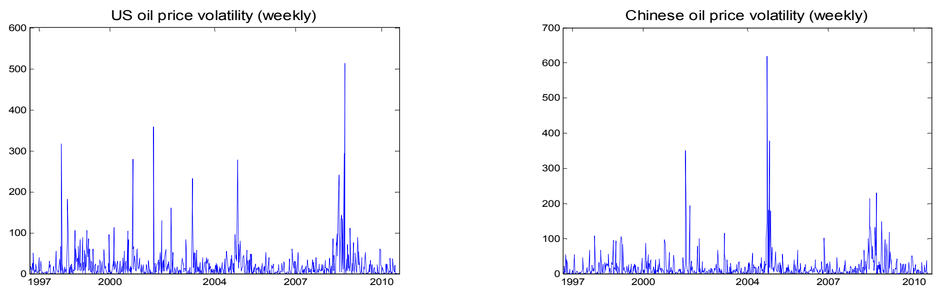

Fig.2 Plots of oil price volatility for US (left) and Chinese markets (right).

Neural Network based on GARCH(p,q). The neural network uses the following mathematical forms in Eq.3 to approximate volatility based on GARCH(p,q) model defined in Eq. 2.

$$\sigma_t^2 = f(X_{t-1}, a, b) + \delta_t = a_0 + \sum_{j=1}^{n} a_j \,.\, F\left(\sum_{i=1}^{m} b_{0j} + b_{ij} x_{ij}\right) + \delta_t \quad (3)$$

where F is a logistic transfer function defined as $F(y) = 1/(1 + \exp(y))$ and a_j: the jth element of vector of coefficients (or weights) from the hidden layer to output layer units. Here $b = (b_{ij})$ is matrix of coefficients from the input to hidden layer units. Input vector X_{t-1} denotes$(\varepsilon_{t-1}^2, \ldots, \varepsilon_{t-p}^2, \ldots, \sigma_{t-1}^2, \ \ldots, \sigma_{t-q}^2)$. Fig.1 displays the architecture of our NN-GARCH(p,q) model. The input vectors $X_{t-1} = (\varepsilon_{t-1}^2, \ldots, \varepsilon_{t-p}^2, \ldots, \sigma_{t-1}^2, \ldots, \sigma_{t-q}^2)$ can be obtained by taking $\varepsilon_{t-l}^2 = y_{t-l}^2$ and $\sigma_{t-l}^2 = \frac{1}{5}\sum_{k=0}^{4} y_{t-l-k}^2$ as in [14]. One step-ahead forecast by the NN-GARCH(p,q) is $\sigma_{t+1}^2 = \hat{\sigma}_t^2 = \hat{f}(X_t, \hat{a}, \hat{b})$.

Training and Forecasting design. We first train the NN based GARCH(p,q) model by building a network, including determining the numbers of nodes and estimating their biases and weights. Back propagation algorithm is used in this training as it is very simple and widely used. We set h=1,2,3,4 for the number of hidden layers to fit and test the proposed models with maximum rate of convergence, 1000 iterations. To obtain optimal hidden-layer-networks, we divide the in-sample data into two non-overlapping subsamples(75% for the first, and 25% the second). The first subsample is used to estimate the weights or parameters of neural network. The so-built network is then applied in the second subsample to test its predictive accuracy. We repeat this process of cross-validation to build the volatility models for nine combinations of p=1,2,3 and q=1,2,3. Therefore, we obtain nine different combinations of NN-GARCH(p,q) models say, NN-GARCH(1,1),NN-GARCH(1,2), …, NN-GARCH(3,3). Now, to choose the most preferable model for these oil price volatilities, we use the remaining out-of-sample data (100 points) to forecast each of the nine models; and the forecasted values are compared with one another. We employ two measurements, HMSE and HMAE defined as below to check the accuracy of the models. HMSE $= \frac{1}{T}\sum_{t=1}^{T}(1 - y_t^2/\hat{\sigma}_t^2)^2$, and HMAE $= \frac{1}{T}\sum_{t=1}^{T}|1 - y_t^2/\hat{\sigma}_t^2|$.

Experimental Results

From the summary statistics of log return rate y_t in Table 1, we can see that both time series exhibit negative skewed and excess kurtosis. The high value of Jarque Bera statistic shows that the two series are not normal. The Ljung Box statistic and Engle-ARCH test significantly rejects the hypothesis of no ARCH effect level, indicating the presence of time-varying volatility. Hence, it is valid and appropriate to fit volatility of these two time series based on the ARCH/GARCH typed models. Tables 2 and 3 illustrate the experimental results. For both US and Chinese markets, there are three networks with two hidden layers and six networks with three hidden layers. Here, we report only the weight estimates of four optimal models obtained from the training and testing results.

US market

NN3-GARCH(1,1): b_{01}= -7.88, b_{11}= -8.36, b_{21}= -22.79, b_{02} = 0.75, b_{12}= 5.29, b_{22} = 21.80, b_{03}= -15.09, b_{13}= -5.27, b_{23}= -87.67, a_0= 29.82, a_1= 32.41, a_2= -8.36, a_3= 9.41.

NN2-GARCH(2,2): b_{01}= -0.57, b_{11}= 3.25, b_{21}= 0.23, b_{31}= 3.06, b_{41}= 1.90, b_{02} = -0.51, b_{12} = -4.10, b_{22}=-5.40, b_{32}= -5.47, b_{42}= -6.49, a_0= 12.32, a_1= 8.99, a_2= 8.90.

Chinese Market

NN2-GARCH(1,1): b_{01}= 1.84, b_{11} = -0.01, b_{21}= -0.03, b_{02} = -3.47, b_{12}= -21.51, b_{22}= -8.76, b_{03}= 77.79, b_{13}= 0.03, b_{23}= -0.53, a_0= 188.98, a_1= -126.60, a_2= 27.17.

NN2-GARCH(3,1): b_{01}= -7.8 , b_{11} = -0.80, b_{21}= -14.70, b_{31}= -2.41, b_{41}= -1.41, b_{02}= 26.94, b_{12}= 6.60, b_{22}= 5.95, b_{32}= 1.31, b_{42}= 10.52, a_0= 33.14, a_1= 17.46, a_2= -14.69.

We also fit normal GARCH(p,q) with combinations (p=1,2,3 and q=1,2,3) to both data for comparative purpose. However, only GARCH(1,1) outperforms the other 8 models. The estimation and forecasting results of GARCH(1,1) are shown in Table 2 and Table 3 respectively. Fig.3 plots forecast values of volatility by the hybrid models, NN-GARCH(1,1) against actual volatility and normal GARCH(1,1) model. The other hybrid models are not shown for the sake of convenient viewing. These plots imply that the hybrid approaches yield improved results since they can capture more extreme values and are more flexible than the normal GARCH model.

Table 1. Summary statistics of y_t.

	US	China
Sample size	730	728
Minimum	-18.9435	-24.888
Maximum	22.6663	15.1944
Mean	0.18364	0.18139
Std. Deviation	4.53794	4.24382
Skewness	-0.3923	-0.62161
Kurtosis	4.92311	5.92963
Jarque-Bera	132.886	310.331
LB.Q(y_t^2)(20)	153.867	203.427
LM.ARCH (20)	79.763	116.096

Table 2. Normal GARCH(1,1) estimation

Parameters	US	China
μ	0.2607[0.171]	0.2243[0.152]
ω	1.4910[0.686]	2.7603[0.775]
α	0.0823[0.022]	0.1822[0.033]
β	0.8486[0.051]	0.6605[0.065]
Log(L)	-1831.6	-1756.5
AIC	3671.2	3520.9
BIC	3689.0	3538.7
Note: [ ] denotes standard error.		

Conclusion

We model oil price volatility by using GARCH(p,q) combined with Neural Network. Using two markets of US and China oil prices, nine different combinations of the combined models, NN-GARCH(p,q), are obtained by using Back-Propagation algorithm in the frame work of cross-validation technique. Then three points can be concluded. First, the training results show that most of the networks require three hidden layers. Second, the out-of-sample forecasting results indicate that all the proposed hybrid models, NN-GARCH(p,q) perform better than the normal GARCH(1,1) model for all cases. Finally, among nine models, NN3-GARCH(1,1) (with three hidden layers) and NN2-GARCH(2,2) (with two hidden layers) outperform the remaining models for US market, while, NN2-GARCH(1,1) and NN2-GARCH(3,1) (with two hidden layers) are superior in Chinese case.

Table 3. Out-of-sample Forecasting Results

US	HMSE	HMAE	China	HMSE	HMAE
NN3-GARCH(1,1)	**0.46171**	**0.50402**	NN2-GARCH(1,1)	**0.51173**	**0.53990**
NN3-GARCH(1,2)	0.59827	0.48677	NN3-GARCH(1,2)	0.60919	0.53825
NN3-GARCH(2,1)	0.56437	0.47513	NN3-GARCH(2,1)	0.69578	0.58006
NN2-GARCH(2,2)	**0.49773**	**0.45346**	NN3-GARCH(2,2)	0.73620	0.62222
NN2-GARCH(2,3)	0.65572	0.50281	NN2-GARCH(2,3)	0.74395	0.61461
NN3-GARCH(3,2)	0.56432	0.47278	NN3-GARCH(3,2)	0.73325	0.61190
NN2-GARCH(1,3)	0.51302	0.53352	NN2-GARCH(1,3)	0.76047	0.68583
NN3-GARCH(3,1)	0.56551	0.47390	NN2-GARCH(3,1)	**0.53434**	**0.52785**
NN3-GARCH(3,3)	0.60935	0.48826	NN3-GARCH(3,3)	0.77900	0.61943
GARCH(1,1)	0.74868	0.74719	GARCH(1,1)	0.76059	0.74838

Note: NN3-GARCH(1,1) and NN2-GARCH(2,2) built by network with 3 and 2 hidden layers, respectively. They both outperform the other models in US case. NN2-GARCH(1,1) and NN2-GARCH(3,1) built by the same 2 hidden layer networks. They both outperform the other models in Chinese case.

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References:

[1] S. Rafiqa and R. Salim: Resources Policy Vol. 34 (2009), p.121-132.

[2] R.F.Engle: Econometrica Vol. 50 (1982), p. 987-1008.

[3] T. Bollerslev: Journal of Econometrics Vol. 31 (1986), p. 307-327.

[4] P. Sadorsky: Energy Economics Vol. 28 (2006), p. 467-488.

[5] P.K. Narayan and S. Narayan: Energy Policy Vol. 35 (2007), p. 6549-6553.

[6] S.H. Kang, S.M. Kang and S.M. Yoon: Energy Economics Vol. 31 (2009), p. 119-125.

[7] C.W. Cheong: Energy Policy Vol. 37 (2009), p. 2346-2355.

[8] Y. Wei, Y.D. Wang and D.S. Huang: Energy Economics Vol. 32 (2010), p. 1477-1484.

[9] B.D. Ripley: In Networks and Chaos- Statistical and Probabilistic Aspects. eds O. E. Barndorff-Nielsen, J. L. Jensen and W. S. Kendall, Chapman and Hall, London (1993).

[10] S. Haykin: *Neural networks* (Prentice Hall, Englewood cliffs 1999).

[11] R.G. Donaldson and M. Kamstra: Journal of Empirical Finance Vol. 4 (1997), p. 17-46.

[12] C.L. Dunis and X. Huang: Journal of Forecasting Vol. 13(2002), p. 317-354.

[13] M. Bildirici and O.O. Ersin: Expert Systems with Applications Vol. 36 (2009), p. 7355-7362

[14] F. Perez-Cruz, J.A. Afonso-Rodriguez and J. Giner: Journal of Quantitative Finance Vol. 3 (2003), p. 163-172.

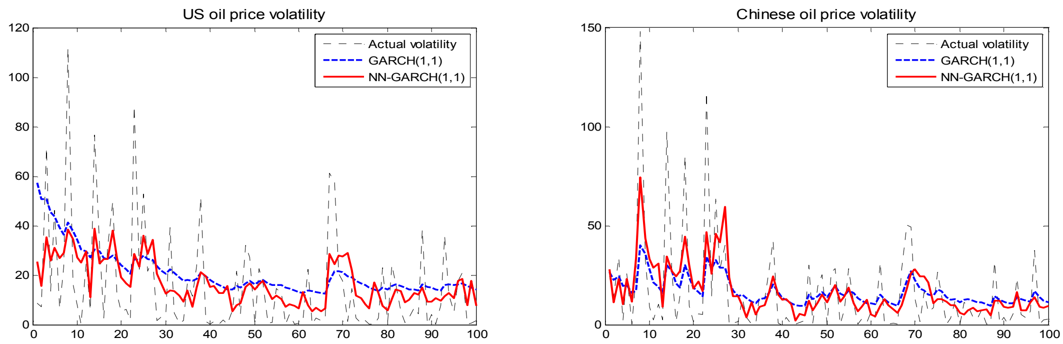

Figure 3. Plots of Volatility Forecasting (US, Left; China, Right).

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