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Forecasting volatility of oil price using an artificial neural network-GARCH model

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ABSTRACT

This paper builds on previous research and seeks to determine whether improvements can be achieved in the forecasting of oil price volatility by using a hybrid model and incorporating financial variables. The main conclusion is that the hybrid model increases the volatility forecasting precision by 30% over previous models as measured by a heteroscedasticity-adjusted mean squared error (HMSE) model. Key financial variables included in the model that improved the prediction are the Euro/Dollar and Yen/Dollar exchange rates, and the DJIA and FTSE stock market indexes.

1. Introduction

The spot price for oil is well off from its historic high of $145 per barrel trading under $40 a barrel for crude oil for the first quarter of 2016. The result of the steep drop in price per barrel makes the extraction from some sources of oil unattractive; for instance, the oil sands in Alberta or fracturing in the Dakotas. Recent growth in the developed world post-economic crises is largely reflected in the rise in the value of the stock market as demonstrated by record highs of the Dow Jones Industrial Average. The increased production of oil in the United States and the large available reserves led to legislative changes that allow domestic oil production to be exported from the United States for the first time in 40 years. Furthermore, Goldman Sachs recently reported that it expects oil prices to further tumble if OPEC stays its course; down more than 42% in 2015, 100,000 workers have already been displaced. While one might expect that the low oil prices are good for consumers who will pay less at the pump, the result has been an upsurge of lower fuel efficient vehicles in the United States; some authors have suggested that the upsurge is directly related to American's 'love' of large vehicles and the lower fuel prices affords a greater opportunity of ownership of them (e.g. Dreibus, 2016; Hulac, 2015; Isidore, 2015).

Given the overall volatility in the spot and futures prices of oil and the overall impact that these prices have on national and global economies, the ability to forecast the volatility of these security prices is of significant importance for those producing oil as well as those investing. In this context, the ability to forecast oil price (spot and futures) volatility with greater precision is not only important for commodity markets, but also for the world economy. The common approach to forecasting is to apply Generalized Autoregressive Conditional Heteroscedasticity (GARCH) to model volatility; however, some studies have found greater forecast accuracy by applying an Artificial Neural Network (ANN) method (e.g. Kristjanpoller & Minutolo, 2015).

Many of the studies that model oil price volatility focus on explaining the behavior of the analyzed sample without measuring the capability of forecasting volatility outside of the sample period. Econometric models, and in particular time-series models, are often used to model futures oil prices based on historical data and as such focus on curve fitting rather than actual forecasting (e.g. Lanza et al., 2005; Pindyck, 1999; Radchenko, 2005). While traditional models explain behavior that has taken place *post hoc*, our approach offers predictive capabilities *ex ante*. The results of this study are useful in improving the prediction of oil spot price and oil futures price volatility. These findings are significant for government agents in countries with economies strongly dependent upon oil production and exports as oil price and volatility impacts the overall economy. Additionally, this model has added value for investors wanting to make investment decisions in the commodity market (spot and futures) in order to achieve better asset allocation and portfolio diversification.

Studies that consider the economic impacts that movement of fuel prices has, particularly oil, are diverse. Researchers have

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considered effects of fuel price movement on GDP (Cologni & Manera, 2009; Gronwald, 2008; Jimenez-Rodriguez & Sanchez, 2005; Narayan & Smyth, 2007), inflation (Chen, 2009; Cologni & Manera, 2008; Doroodian & Boyd, 2003; Farzanegan & Markwardt, 2009), reduction of investment (Hamilton, 2003; Rafiq, Salim, & Bloch, 2009), economic cycle (Gisser & Goodwin, 1986; Jones, Leiby, & Paik, 2004), the price movements of other future energy contracts (Bhar & Hamori, 2005; Ewing, Malik, & Ozfidan, 2002), and stock prices (Huang, Masulis, & Stoll, 1996; Sadorsky, 2003). In recent years, some research has focused on modeling and forecasting volatility in financial series, since this is crucial for market characterization, portfolio optimization, and asset valuation; oil is no exception. There are numerous studies whose focus is on oil, whether it is the analysis of its spot price, futures price, or volatility (e.g. McAleer & Sequeira, 2004; Ratti & Hasan, 2013; and, Sequeira & McAleer, 2000). In this study, we extend the research streams that consider economic impacts on spot and futures oil price volatility using an ANN-GARCH model to demonstrate improvements in precision over classical forecasting models.

In the literature, many models have been used to forecast volatility, but the most widely used are the ARCH models proposed by Engle (1982), and then generalized by Bollerslev (1986); these approaches have led to significant improvements in the modeling of time series. Agnolucci (2009) analyzed the predictive power of implied volatility in oil derivatives, concluding that heteroscedastic models have better performances. In their review of the literature, Hou and Suardi (2011) argued that studies demonstrate that GARCH models are more appropriate for out-of-sample forecasting, but none of the models in this family are consistently shown to be the best. There are various studies using GARCH models and derivatives to predict oil market volatility (Aloui & Mabrouk, 2010; Arouri, Jouini, & Nguyen, 2011; Cheong, 2009; Hou & Suardi, 2011; Mohammadi & Su, 2010; Narayan & Narayan, 2007; Sadorsky, 2006; Wei, Wang, & Huang, 2010).

Some studies have incorporated artificial intelligence to forecast the volatility. Donaldson and Kamstra (1997) focused their work on modeling the volatility in a way that can capture the most important asymmetric effect, using distinct GARCH families combined with Neural Network. Furthermore, they analyzed the strength of the modeling out of sample. Wang (2009) used a similar approach in terms of methodology, but applied the analysis with GJR-GARCH and Grey-GARCH in conjunction with Neural Networks. Monfared and Enke (2014) also used this approach, but with a different time span and rolling window.

Dhamija and Bhalla (2010) used data from a period of financial meltdown in order to demonstrate that the use of GARCH and neural network is capable to determine the long-run non-linearity of the data. Vejendla and Enke (2013a) compares the prediction of volatility between a GARCH model and historical volatility model, in conjunction with ANN and RNN models. They first evaluated which AI is better for prediction, and then combine the better AI with both econometric models, in order to determine, using MSE, which is better. They conclude that the prediction of the GARCH model is better, but the analysis relies strongly on the data set. Furthermore, Vejendla and Enke (2013b) applied the same methodology describe previously but in the options market. Specifically, they compare GARCH, FNN and RNN over several data sets and determined which is better for forecasting. In particular for the data analyses, the GARCH model gives better results. Monfared and Enke (2015) proposed the use of an adaptive Neural Network filter to forecast the error of the GARCH models, and then applied this to the forecast of the GARCH in order to improve the forecasting on the later.

In research regarding the use of artificial intelligence to predict financial series, Azadeh, Moghaddam, Khakzad, and Ebrahimipour (2012) applied a flexible algorithm based on an artificial Neural Network and fuzzy regression to predict oil price, concluding that the ANN model achieves the best predictions measured in terms of mean absolute percentage error (MAPE). Boyacioglu and Avci (2010) applied an adaptive neural fuzzy inference system (ANFIS) to the Istanbul stock market to predict earnings per share, concluding that this method was successful for monthly forecasting. Svalina et al. (2013), using ANFIS to predict the closing price in the Zagreb Stock Market index, obtained information that is useful for predicting within the boundaries of the study. Bildirici and Ersin (2009) used a Neural Network model along with different GARCH-type models and applied them to the Istanbul stock market, showing an improvement in the RMSE in most of the used models. Hajizadeh, Seifi, Zarandi, and Turksen (2012) used two hybrid Neural Network models in order to improve the GARCH-type forecasts using explanatory variables to explain the variability of the returns of the S&P500, obtaining better results than the GARCH models when compared to the realized volatility. Lahmiri & Boukadoum (2014) took a different approach in which they assume a different distribution on the error part of the GARCH model, in order to capture different statistical characteristics. Thus, they assume a normal distribution to capture normality, a normalized t-student distribution to capture skewness, and a GED distribution to capture kurtosis; they work specifically with EGARCH in combination with Neural Networks. Kala, Shukla & Tiwari (2010) modeled volatility focusing on capturing the most important asymmetric effect, with different GARCH, and each of them improved with a Neural Network and genetic algorithms. They used the Neural Networks specifically to improve the prediction of the EGARCH, and then the genetic algorithm was used to optimize the weights and bias of the later.

More recently, Wang and Wu (2012) modeled the dynamics of price volatility in the energy market, essentially the spot price of crude oil (West Texas Intermediate), conventional gasoline (New York Harbor), heating oil (New York Harbor), and jet fuel (U.S. Gulf Coast), concluding that multivariate heteroscedastic models show better performance than univariate models. Sadorsky (2006) concluded that GARCH models perform better than multivariate models in the prediction of the price of oil and unleaded gasoline. Liu and Wan (2012) analyzed the volatility of fuel oil futures prices in Shanghai, concluding that the best predictions in forecasting daily and *intra-day* volatility are obtained by the GARCH (1,1) and EGARCH, when compared to other GARCH models.

This paper contributes to the literature on fuel price volatility modeling in several ways. First, it extends previous research in the hybrid modeling domain, namely Kristjanpoller and Minutolo (2015), to the area of oil price volatility and includes a Fractionally Integrated Generalized AutoRegressive Conditionally Heteroscedastic (FIGARCH) approach. While there are some studies about predicting oil price with ANN (Azadeh et al., 2012; Bildirici & Ersin, 2013; Godarzi, Amiri, Talaei, & Jamasb, 2014; Jammazi & Aloui, 2012), none have considered volatility. This paper differs from the previous literature in four aspects. First, we use the exchange rate and the stock market index variations to improve the forecast of crude oil. Specifically, we use the exchange rates in USD base because the oil industry is greatly affected by and trades in that currency and therefore, if it changes it may cause a shock in the price of crude oil. Also, there is a known relationship between oil price and the stock markets, for this reason the Dow Jones Industrial Average and the Financial Time Stock are added. Second, in order to test and extend the forecast capability of the model, it will be tested in three different forecast horizon (14, 21 and 28 days). Third we measure the improvement of the volatility forecasting through the use of evaluation criteria using loss function adjusted by heteroscedasticity. Finally, we propose a new way of selecting the explanatory variables for inclusion in the forecast model.

The remainder of the paper is structured as follows. In the next section, we present our methodology and the algorithms used. Then, we discuss the data followed by the empirical results. Finally, we discuss the findings with limitations and potential future extensions of this work.

2. Methodology

To forecast volatility, the methodology used in this study follows a hybrid model; namely, an Artificial Neural Network – Generalized Autoregressive Conditional Heteroscedasticity (ANN-GARCH) model. This model predicts the volatility of commodity price by first employing a GARCH (1,1) application. The forecasts from the GARCH (1,1) model, along with financial time series data, are used as inputs in the ANN to improve the overall commodity price forecast. Kristjanpoller, Fadic, and Minutolo (2014) recently used this model to predict the volatility of six Latin American stock markets, demonstrating improved prediction performance.

To illustrate the application, suppose P_t is an index of prices from a financial series, and r_t its return or percentage price variation, where the index t denotes an observation of the daily closing price giving in Eq. (1).

$$r_t = \log P_t - \log P_{t-1} \tag{1}$$

The forecasting objective of the model is the realized volatility in the pricing, and it is computed as sample variance log returns in a 21-day window into the future (approximately one month of transactions), as shown by Eq. (2).

$$RV_t = \frac{1}{21}\sum_{i=t+1}^{t+21}(r_i - \bar{r}_t)^2 \tag{2}$$

In this study, a GARCH (1,1) model is used to forecast the volatility attributed to heteroscedasticity, using a moving window length of 252 days back (one year of transactions); in addition, an autoregressive model of the order 1 is used for the mean equation (Eq. (3))

$$\begin{aligned} r_t &= c + \theta_1 r_{t-1} + \varepsilon_t\sigma_t \\ \sigma_t^2 &= \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \end{aligned} \tag{3}$$

Artificial Neural Networks are a powerful, non-parametric tool used for signal filtering, pattern recognition, and interpolation, as well as many other applications. Among their characteristics, ANN are also able to tolerate data with errors and find nonlinear associations between model parameters. Moreover, one of its major advantages over other econometric methods is that it is not necessary to consider the model's functionality, meaning that assumptions about the functional relationship among the variables are not necessary. However, as with all models, it is necessary to incorporate the appropriate variables in order to make a good estimate.

Each Neural Network connects a group of input variables $\{x_i\}$, $i = 1, \ldots, k$ with a group of one or more output variables $\{y_j\}$, $j = 1, \ldots, k$ and zero, one, or more, so-called hidden layers as illustrated in Fig. 1. Neurons are connected between the layers for connections that are activated by reaching a threshold, because the evaluation of the function of transfer is based on the input parameters. Each layer can have a different number of neurons. The input and output can be continuous, discrete, and binary variables, or a combination of all of these.

This study uses the back-propagation algorithm. This is an algorithm for supervised learning which seeks to minimize the quadratic error by descent of the maximum gradient. It is based on backpropagation of errors model, Rumenlhart, Hinton, and Williams (1986).

To estimate the Neural Network Model, it is necessary to define the input variables, the characteristic parameters of the network, and the length of the window available. In this case, the independent variables used as inputs for the ANN portion of the model are the GARCH forecast estimates, the square of the oil price return (as proxy of the volatility), and the financial time series of the daily variations of Euro/Dollar (EUR) and Dollar/Yen (YEN) exchange rates as the main worldwide exchange rates, as well as the stock market index returns of the Dow Jones Industrial Average (DJIA) and the Financial Time Stock Exchange (FTSE). The EUR and YEN were selected because is an established relationship between oil prices and these exchange rates (Golub, 1983). The evidence of this relationship has been reinforced by Akram (2009), Chen and Chen (2007), Reboredo (2012), Sadorsky (2000), Zhang, Fan, Tsai, and Wei (2008), Benhmad (2012) and Basher, Haug, and Sadorsky (2012). However, the relationship between the oil market and the stock markets has a longer history and recently there have been numerous studies approaching the nature of the relationship with different models: Arouri and Nguyen (2010); Fayyad and Daly (2011); Filis, Degiannakis, and Floros (2011); Wang, Wu, and Yang (2013); and, Basher et al. (2012). Finally, Mollick and Assefa (2013), analyzing the period 1999–2011 with respect to oil price, the main American stock market indexes, exchange rates and others financial variables finding influences between the oil, stock and exchange rate markets. All of these studies show the importance of the stock market and the exchange rate into the behavior of oil price.

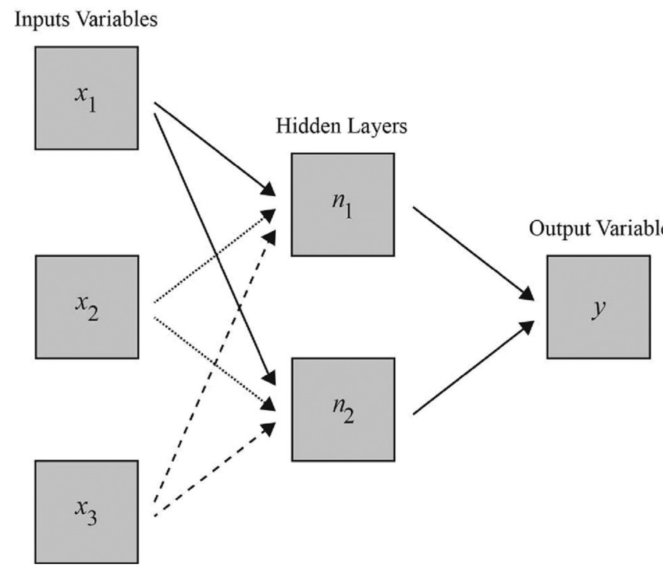

Fig. 1. Illustration of a Neural Network.

The initial parameters of the ANN are three layers with five neurons per layer. The realized volatility to forecast is t+22, which implies the standard deviation calculated 22 days from t, taking the last 21 data (unknown t) to calculate it. The rolling window length is 252 days, roughly one trading year. In all tested models, the GARCH forecast and the square of oil price variation are included. Later, we present our findings testing various neuron and layer combinations and the outcomes that resulted in this model.

The first models are built from two input series: the GARCH forecast and the square of the oil price return. These two input variables are defined as basic, because the GARCH forecast is the variable that is improved through the ANN-GARCH, and the square oil price return is a good predictor for the realized volatility. Once the initial model is constructed, run, and stable, the following models are built including the financial series data (DJIA, FTSE, and currency). After this analysis, in order to find the optimal architecture of the artificial Neural Network, the period of the realized volatility to the forecast, the layer number, and the neuron

Table 1
Descriptive statistics of the logarithmic returns of oil prices.

	Mean (%)	Standard deviation (%)	Min (%)	Max (%)	Skewness	Kurtosis	Normality test	ADF
Spot	0.0455	2.3484	−13.07	21.28	0.12	8.74	4086.30	−56.65
Future	0.0463	2.3245	−13.07	16.41	0.00	7.71	2718.80	−56.45

Note: The Normality Test is the Jarque–Bera test, which has a $\chi^2(q)$ distribution with 2degrees of freedom under the null hypothesis of normally distributed error. The 5% critical value is therefore 5.99. The Augmented Dickey Fuller test tests up to the twelfth lag and the 5% critical value is −2.86.

Table 2
Descriptive statistics of the independent variables.

Variable	Mean (%)	Standard deviation (%)	Min (%)	Max (%)	Skewness	Kurtosis	Normality test	ADF
DJIA	0.0154	1.1915	−8.201	10.508	0.0379	11.83	10,434.48	−44.01
FTSE	0.0041	1.2485	−9.265	9.384	−0.0922	9.79	6163.54	−26.01
EUR	0.0130	0.4329	−2.123	2.531	−0.0988	5.35	7401.83	−26.06
JPY	−0.0018	0.6532	−4.583	3.832	−0.1497	6.38	1539.45	−58.06

Note: The Normality Test is the Jarque–Bera test, which has a $\chi^2(q)$ distribution with 2 degrees of freedom under the null hypothesis of normally distributed error. The 5% critical value is therefore 5.99. The Augmented Dickey Fuller test tests up to the twelfth lag and the 5% critical value is −2.86.

number are modified. Furthermore, to determine the impact of the financial time series used, their combination as input variables are changed. In particular, the volatility forecast is varied to 21 days, 14 days, and 28 days. These models are applied to forecast the realized volatility of oil spot prices and oil futures prices.

Expanding upon Kristjanpoller et al. (2014), the first ANN-GARCH model includes the GARCH forecast and the squared oil price return (spot or futures depending on case) and the other four variables as inputs to the ANN. Furthermore, seeking the best architecture and additive sequence, one variable is added stepwise even if a low number of the variables are shown to support the best performance. This change in the methodology is due to the fact that Kristjanpoller et al. (2014) used the correlation of the volatility and the variables to choose the sequence, while in this paper the sequence is defined by the performance in each round.

To analyze the results, the forecasted values are compared to the realized volatility through some loss functions. The loss functions typically applied are the Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Deviation (MAD or MAE). However, we are grateful to early reviewer comments that pointed out that typical loss function measures apply to linear models while this model is not and therefore requires nonlinear loss measurement. Therefore, we use the heteroscedasticity of the volatility series to measure the loss functions. Following Fuertes, Izzeldin, and Kalotychou (2009), the loss functions used are (HMSE) and the Heteroscedasticity-adjusted MAE (HMAE). The Heteroscedasticity-adjusted MSE is described in Eq. (4) and corresponds to the mean of the squared percentage error.

$$HMSE = \frac{1}{n}\sum_{i=1}^{n}(1-\hat{\sigma}_i^2/RV_i)^2 \tag{4}$$

where $\hat{\sigma}_i^2$ corresponds to the volatility forecast for the time i, RV_i is the actual volatility for the time i and n is the number of forecasted periods.

The Heteroscedasticity-adjusted MAE instead of taking the squared error, takes the absolute error, Eq. (5).

$$HMAE = \frac{1}{n}\sum_{i=1}^{n}|1-\hat{\sigma}_i^2/RV_i| \tag{5}$$

where $\hat{\sigma}_i^2$ corresponds to the volatility forecast for the time i, RV_i is the actual volatility for the time i and n is the number of forecasted periods.

Both indicators demonstrate the relative extent of the error with respect to the objective value through the interday volatility and as Fuertes et al. (2009) defined, these loss functions are adjusted by the heteroscedasticity, a fundamental characteristic of volatility in financial series, and more specifically, of the volatility of the metal price series analyzed.

To compare and test the significance of the ANN-GARCH forecasting, ARFIMA forecasting was used as a benchmark. The ARFIMA is one of the traditional models to predict volatility and has a good performance in comparison with other models (Baillie et al., 1996; Pong et al., 2004; Lux & Kaizoji, 2007). Likewise, the traditional GARCH model forecasts are presented.

3. Data

The data sets analyzed in this paper are the Oil Spot Price and the Oil Futures Price (Generic 1st 'CL' Future) from Bloomberg. The sample period for the price data is from July 2002 to May 2014. Table 1 shows some descriptive statistics for the Oil Spot and Futures Price returns. In both cases, the daily mean return is close to 0.045% and the standard deviation is around 2.3%. The Augmented Dickey Fuller test (ADF) is used to analyze the stationarity, which turns out to be significant at 1% for the series. Therefore, we may conclude that the series is stationary, and thus can be used to model.

The Kurtosis is much higher than 3 (value for which the series is usually Mesokurtic), indicating that the series presents a high degree of concentration around the central values of the variable. This shows that fat-tailed distributions are necessary to correctly describe the conditional distribution of the returns.

The skewness is close to zero, showing that the series are close to a symmetric. The Jarque–Bera Normality Test indicates that model errors are not normally distributed, implying that the empirical distribution of the daily returns of the oil prices exhibit significantly heavier tails than in a normal distribution.

The descriptive statistics of the independent variables are shown in Table 2. All the variables have a positive mean except the Japanese Yen. The oil price shows a high daily return and also a high standard deviation. All series are stationary.

In Fig. 2, the evolution of the oil prices and the 21-day variance is plotted in order to observe the behavior of the spot and futures oil price. The subprime crisis around 2008 is clear when both prices drop sharply. Before this crisis, the oil prices had an upward trend since 1999 and subsequently also show an upward trend until 2014 (2.A and 2.B). The figures for returns and variance show a high volatility during the subprime crisis. There also are certain volatility clusters in 2002, 2003, 2004, and 2009. The be-

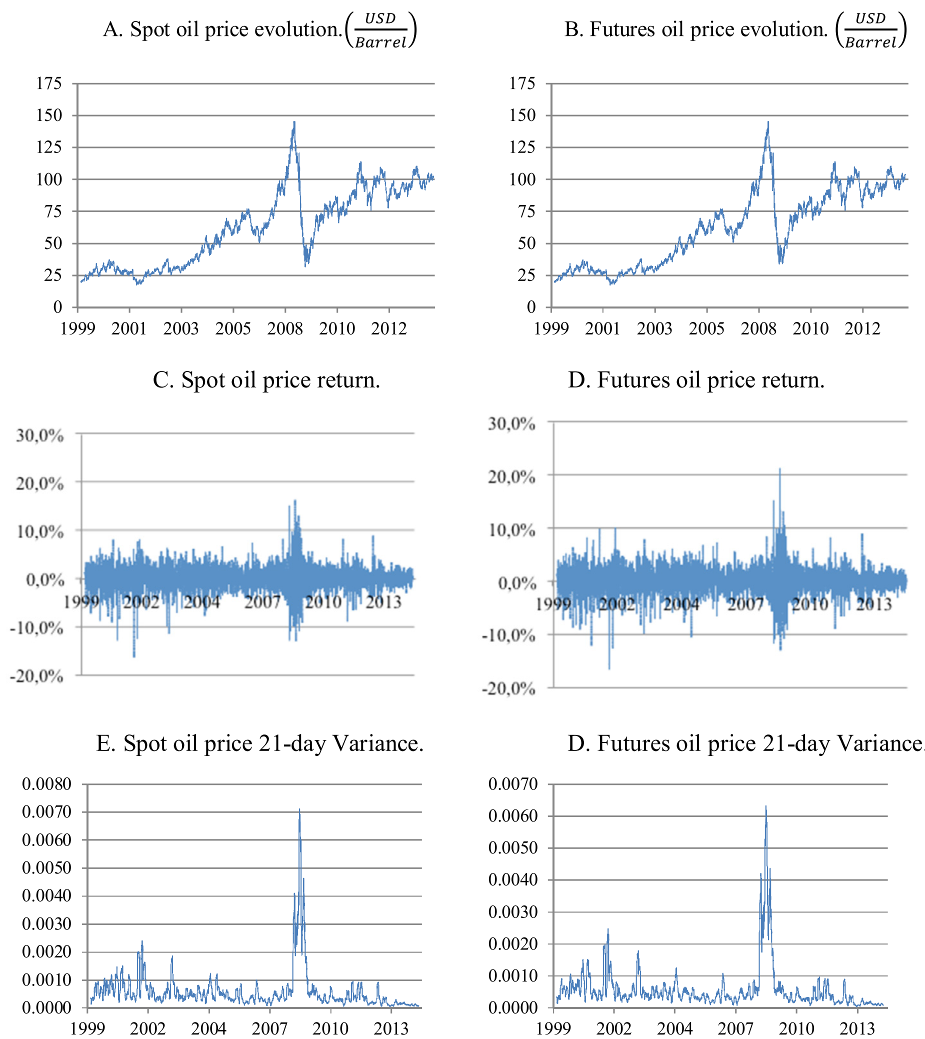

Fig. 2. Behavior of the spot and futures oil price.

Table 3
Performance results for forecast models ARFIMA and GARCH (21 days).

Models	Spot price volatility (21d)		Futures price volatility (21d)	
	HMSE	HMAE	HMSE	HMAE
ARFIMA	1.1146	0.7006	0.9566	0.6547
GARCH	0.6013	0.6431	0.5728	0.6329

havior of the price, return, and variance for spot and futures price are similar.

4. Empirical results

The first forecasts that were performed were those from the ARFIMA model and the GARCH model so as to use them as a benchmark in order to compare the forecasts from the hybrid model. In Table 3, the obtained results of the loss functions for volatility forecasting at 21 days are presented for the spot price and futures oil price. It can be observed that the GARCH model is superior on average for both loss functions, although the difference is lower in the HMAE.

After these results, the forecast was performed of the ANN-GARCH with the base configuration of 2 layers and 5 neurons per layer. As an input, the base of two variables was used (the squared return and the GARCH prediction), and the other variables were incorporated stepwise according to correlation. The input order of these variables is DJIA, EUR, FTSE, and finally, JPY.

The best result of the forecasting of oil spot price volatility by the ANN-GARCH reduced the HMSE by 30.64%, constituting a significant improvement in forecasting precision; while in the case of the oil futures price volatility model, the ANN-GARCH reduced the MAPE from 0.5728% to 0.4021%, a 29.79% reduction. In both cases, the best model is achieved when four variables are used as inputs for the ANN (GARCH prediction, squared oil price return, DJIA, and EUR). The results are presented in Table 4. It can be seen that the best models with respect to HMSE are also the best models with respect to HMAE.

When the forecast horizon is changed, the best performances are achieved by the GARCH model to predict the volatility 14-days ahead for both prices (spot and futures). In the case of the volatility 28-days ahead, the GARCH has a better performance in forecasts, but the ARFIMA has better results in the futures price volatility measured by the HMAE. The results are presented in Table 5.

For each case, the ANN-GARCH is run incorporating the variables stepwise. The results demonstrate that for oil spot price volatility, the ANN-GARCH improves the forecasting HMSE by 22.00% and 39.09%, for the 14-day and 21-day price return volatility. In both cases, the higher reduction is achieved with 4 variables as inputs. In the case of oil futures price return volatility, the HMSE is reduced by 17.56% and 36.52%, with the ANN-GARCH model for the horizon at 14 days and 28 days, using all the variables as

Table 4
Performance results for forecast models ANN GARCH (2 layers, 5 neurons per layer).

Models	Spot price volatility (21d)				Futures price volatility (21d)			
	HMSE	Var (%)	HMAE	Var (%)	HMSE	Var (%)	HMAE	Var (%)
ANN-GARCH 2 VARS	0.4266	−29.06	0.5735	−10.81	0.4041	−29.45	0.5596	−11.58
ANN-GARCH 3 VARS	0.4207	−30.04	0.5734	−10.83	0.4034	−29.57	0.5577	−11.89
ANN-GARCH 4 VARS	**0.4171**	−**30.64**	**0.5713**	−**11.16**	**0.4021**	−**29.79**	**0.5565**	−**12.08**
ANN-GARCH 5 VARS	0.4279	−28.84	0.5740	−10.74	0.4157	−27.42	0.5651	−10.72
ANN-GARCH 6 VARS	0.4237	−29.54	0.5752	−10.56	0.4106	−28.31	0.5628	−11.08

For each model, the number of forecasts is 2940. The number of variables in the model means the variables used as inputs in the ANN. The variation is calculated based on the best model between the ARFIMA and GARCH. The best performances are shown in bold letters.

Table 5
Performance results for forecasting models ARFIMA and GARCH (14 days and 28 days).

Models	Spot price volatility (14d)		Futures price volatility (14d)	
	HMSE	HMAE	HMSE	HMAE
ARFIMA	1.8324	0.8210	1.5222	0.7627
GARCH	0.6872	0.5996	0.5946	0.5804
	Spot price volatility (28d)		Futures price volatility (28d)	
Models	HMSE	HMAE	HMSE	HMAE
ARFIMA	0.9957	0.6621	0.8099	0.6077
GARCH	0.7257	0.7183	0.6852	0.7076

inputs. The results are presented in Table 6. It can be seen that the best models with respect to HMSE are also the best models with respect to HMAE. However, the improvement in HMAE is much smaller, indicating that the improvements produced by the hybrid model are to a greater extent in the high volatility clusters.

To find the best architecture of the ANN, the forecasts are also completed with differing combination of layers and neurons per layers. All combinations between one to five layers were used by 2, 5, 10, and 20 neurons per layer. To test the performance and make the best model clear, the Model Confidence Set (MCS) was applied (Hansen, Lunde, & Nason, 2003; Hansen, Lunde, & Nason, 2011). In the case of the spot price return volatility prediction, the results indicate that the best ANN architecture to forecast the 21-day volatility is 3 layers with 10 neurons per layer, reducing the HMSE by 31% and showing significant improvement at 5% due to the MCS test. For the 14-day volatility, the best configuration is 5 layers with 20 neurons per layer, but this is not significantly different from the GARCH model forecasts. The best model to predict 28-day volatility is one layer with only 2 neurons per layer, reducing the HMSE by 41% and with a difference significance of less than 1%. When the best architectures are compared with the base case (2×5) forecasting, the improvements for the 21-day and 28-day volatilities are 0.70% and 0.81%, respectively, and these are not significant. However, in the case of 14-day volatility, the improvement is 5.64% and is significant.

In the case of futures oil price volatility, only two architectures are different from the GARCH model at 21 days, 1×5 and 5×10, reducing the HMSE by 35%. For 14-day and 28-day volatility, the best architectures are 3×10 and 4×10, respectively. These architectures reduce the HMSE by 25% in the case of 14 days and 38% for the 28-days, and both are significantly different than the GARCH at 5%. When the best architectures are compared with the base case (2×5) forecasting, the improvement in the 14-day, 21-day, and 28-day volatilities are 5.99%, 7.68%, and 1.13% respectively, and the improvement is significant for the first two cases. The results are presented in Tables 7 and 8.

Finally, to analyze if the best model to predict volatility is achieved when all the variables are used as inputs, the models are recalculated following a new algorithm. The algorithm starts calculating the models with the two fixed variables (GARCH forecasting and square price return) and one of the four other variables (Euro/Dollar, Yen/Dollar, FTSE, and DJIA). Thus, four models are calculated in the first round. The variable associated with the best of these four models (lowest HMSE) is then incorporated as fixed for the next round. In the second round, the models have three fixed variables and new ones are calculated by adding one of the three remaining variables. With this algorithm, the variables are incorporated into the models as they improve the model.

Table 6
Performance results for volatility forecasting at 14 and 28 days by ANN GARCH models (2 layers, 5 neurons per layer).

Models	Spot price volatility (14d)				Future price volatility (14d)			
	HMSE	Var (%)	HMAE	Var (%)	HMSE	Var (%)	HMAE	Var (%)
ANN-GARCH 2 VARS	0.5633	−18.03	0.5885	−1.85	0.5023	−15.51	0.5605	−3.44
ANN-GARCH 3 VARS	0.5638	−17.96	0.5923	−1.22	0.4954	−16.68	0.5590	−3.69
ANN-GARCH 4 VARS	**0.5360**	−**22.00**	**0.5815**	−**3.02**	0.4927	−17.14	0.5600	−3.52
ANN-GARCH 5 VARS	0.5716	−16.82	0.5888	−1.79	0.4982	−16.20	0.5578	−3.89
ANN-GARCH 6 VARS	0.5482	−20.23	0.5894	−1.69	**0.4902**	−**17.56**	**0.5553**	−**4.33**
	Spot price volatility (28d)				Future price volatility (28d)			
Models	HMSE		HMAE	MCS	HMSE		HMAE	
ANN-GARCH 2 VARS	0.4483	−38.23%	0.6052	−15.75%	0.4372	−36.19%	0.5914	−2.68%
ANN-GARCH 3 VARS	0.4521	−37.70%	0.6050	−15.78%	0.4383	−36.03%	0.5934	−2.36%
ANN-GARCH 4 VARS	**0.4420**	−**39.09%**	**0.6009**	−**16.35%**	0.4467	−34.80%	0.5974	−1.69%
ANN-GARCH 5 VARS	0.4515	−37.78%	0.6085	−15.29%	0.4462	−34.88%	0.6003	−1.21%
ANN-GARCH 6 VARS	0.4483	−38.23%	0.6057	−15.69%	**0.4350**	−**36.52%**	**0.5900**	−**2.91%**

For each model, the number of forecasts for 14 days is 2947 and for 28 days is 2933. The number of variables in the model means the variables used as input in the ANN. The variation is calculated based on the best model between the ARFIMA and GARCH. In bold letter are showed the best performance.

Table 7
Performance results for forecast spot price return volatility models for different number of layers and neurons per layer.

ANN		21-days		14-days		28-days	
Layer	Neurons	HMSE	*p*-value	HMSE	*p*-value	HMSE	*p*-value
1	2	0.5187		0.5413		**0.4387**	***
1	5	0.4269	**	0.5123		0.5411	
1	10	0.6503		0.5495		0.5403	
1	20	0.5642		0.6079		0.6358	
2	2	0.4208	**	0.5611		0.4457	***
2	5	0.4171	**	0.5360		0.4420	***
2	10	0.4340	*	0.5316		0.4453	***
2	20	0.4246	**	0.5447		0.4475	***
3	2	0.4170	**	0.5608		0.4479	***
3	5	0.4258	**	0.5337		0.4472	***
3	10	**0.4137**	**	0.5255		0.4517	***
3	20	0.4152	**	0.5308		0.4448	***
4	2	0.4306	**	0.5564		0.4424	***
4	5	0.4193	**	0.5462		0.4455	***
4	10	0.4168	**	0.5263		0.4439	***
4	20	0.4142	**	0.5243		0.4482	***
5	2	0.4265	**	0.5363		0.4441	***
5	5	0.4201	**	0.5289		0.4404	***
5	10	0.4187	**	0.5141		0.4418	***
5	20	0.4154	**	**0.5058**		0.4471	***

***, **, and * mean 1%, 5%, and 10% statistical significance related to *p*-value of the Model Confidence Set, Hansen et al. (2003) and Hansen et al. (2011). Each model is run with the optimal number of variables according to the best base model.

Table 8
Performance results for forecasting futures price return volatility models for different number of layers and neurons per layer.

ANN		21-days		14-days		28-days	
Layer	Neurons	HMSE	p-value	HMSE	*p*-value	HMSE	*p*-value
1	2	0.4870		0.5822		0.4935	*
1	5	**0.3713**	**	0.5382	*	0.6299	
1	10	0.4699		0.5851		0.6142	
1	20	0.4923		0.6843		0.8751	
2	2	0.4121		0.4959	**	0.4401	**
2	5	0.4021		0.4902		0.4350	**
2	10	0.4099		0.5006	**	0.4368	**
2	20	0.4099		0.4872	**	0.4370	**
3	2	0.4109		0.5143	*	0.4358	**
3	5	0.4089		0.5033	**	0.4358	**
3	10	0.4001		**0.4608**	**	0.4367	**
3	20	0.3966		0.4773	**	0.4344	**
4	2	0.4043		0.4979	**	0.4363	**
4	5	0.4070		0.4848	**	0.4352	**
4	10	0.3988		0.4887	**	**0.4301**	**
4	20	0.4110		0.4651	**	0.4322	**
5	2	0.4108		0.4859	**	0.4310	**
5	5	0.4014		0.4795	**	0.4310	**
5	10	0.3894	**	0.4942	**	0.4300	**
5	20	0.4021		0.4729	**	0.4375	**

***, **, and * mean 1%, 5%, and 10% statistical significance related to p-value of the Model Confidence Set, Hansen et al. (2003) and Hansen et al. (2011). Each model is run with the optimal number of variables according to the best base model.

For the 21-day spot price volatility in the first round, the best forecasting results are achieved with the model including the DJIA. For the second round, the DJIA is incorporated as fixed and the best model in the second round includes the EUR return. In the third round, keeping the GARCH forecasts, square price return, DJIA, and EUR returns as fixed variables, the best result comes from the model that incorporates the FTSE. Then, in the fourth round, all the variables are included and the lowest HMSE is achieved in the second stage, demonstrating that the model with four variables (GARCH forecasts, square price return, DJIA, and EUR returns) as inputs is the best. This result is the same for the futures oil price volatility, and both coincide with the best obtained result in the base model.

For the cases of the 14-day and 28-day spot price return volatility, the results show that the best model contains only one variable more than the two fixed variables. In the case of 14-day volatility, this variable is the FTSE, and for 28-day volatility, it is the JPY. The HMSE is reduced by 2.93% and 2.47% with respect to the optimal variable obtained in the base case, respectively. While in the cases of 14-day and 28-day futures price return volatility, the best performances are achieved with all variables, coinciding with the optimal variable obtained in each base case. The results for the different rounds of spot and futures prices are presented in Table 9.

Table 9
Performance results for forecasting models by rounds.

	Spot price return volatility				Futures price return volatility			
	1st round	2nd round	3rd round	4th round	1st round	2nd round	3rd round	4th round
14 days								
DJIA	0.5638	0.5600	0.5716		0.4954			
EUR	0.5564	0.5385			0.5096	0.4927		
FTSE	**0.5326**				0.4969	0.5136	0.4982	
JPY	0.5541	0.5607	0.6133	0.5482	0.5229	0.4944	0.5331	**0.4902**
21 days								
DJIA	0.4207				0.4034			
EUR	0.4290	**0.4171**			0.4083	**0.4021**		
FTSE	0.4280	0.4360	0.4279		0.4085	0.4311	0.4157	
JPY	0.4301	0.4418	0.4375	0.4237	0.4109	0.4181	0.4867	0.4106
28 days								
DJIA	0.4521	0.4516	0.4515		0.4383	0.4576		
EUR	0.4463	0.4428			0.4376	0.4516	0.4462	
FTSE	0.4511	0.4438	0.5684	0.4483	0.4354			
JPY	**0.4375**				0.4375	0.4604	0.4548	**0.4350**

The variable with the lowest HMSE is selected in each round. The best model to predict volatility is shown in bold. For the first, second, and third round, the best model for each round is underlined.

5. Conclusions

This paper has achieved several important functions. First, it extends the body of knowledge about Artificial Neural Networks and their applications. Herein we extended previous applications of ANN-GARCH models that were applied in other financial markets and gold prices to the oil spot and futures price markets. Our results suggest that the ANN-GARCH model may be successful in improving forecasts of volatility and spot price over traditional forecasting models.

Second, this paper develops a method to determine which financial variables are most important in affecting the volatility of oil spot prices and futures prices. The aim is to find the best model to predict volatility beyond the model's historical data. This is extremely important as the global market for crude oil continues to struggle with the persistent and strong downturn in the commodity market. Understanding and predicting the impact in the commodities market through our knowledge of the movement in the independent variables may help political and financial leaders mitigate the overall effect. Furthermore, knowing the magnitude of the movement in the oil commodity market by watching the movement of other variables allows leaders to anticipate other outcomes.

The results from this study demonstrate that the ANN-GARCH model improves the forecasts of the GARCH model by 30.6% for the oil spot price volatility and 29.8% for the oil futures price volatility when using 21 days as a horizon. The best results were demonstrated in the 21-day spot and futures volatility forecasts using the Euro/Dollar and DJIA as input variables to the ANN. Also, for 14-day and 28-day forecasts of futures prices, the results show the best performance is when all variables are included. For 14-day forecasts of spot price volatility and 28-day spot price volatility, the results show the best performance is when only one variable is included along with the two fixed variables (GARCH forecasting and square price return), being the FTSE returns and the JPY variations, respectively.

When the best ANN architecture is applied over the parameters, the results tend to be the same. The best performance is achieved for the case of the spot price return volatility forecast. The results indicate that the best ANN architecture to forecast 21-day volatility is 3 layers and 10 neurons per layer, for 14-day volatility, it is 5 layers with 20 neurons per layer, and for 28-day volatility, it is one layer and only 2 neurons per layer. In the cases of futures oil price volatility, for 21 days, the best architecture is 1×5, and for the 14-day and 28-day volatility, the best are 3×10 and 4×10, respectively. In general, the best architecture improves forecasts in comparison with the base case (2×5). Nonetheless, precision improvement is significant only for 14-day (both spot and futures) and for the 21-day futures price volatility.

One area of promising future research is in the combination of our work with the cost-of-carry theory. The cost-of-carry theory assumes that there is no arbitrage, contracts are held to maturity, the underlying asset is a commodity, carrying costs are net of storage, and risk-free interest rates (McAleer & Sequeira, 2004). Using the ANN-GARCH model developed here, one might be able to better estimate the cost-of carry given the work developed in the literature, thereby developing a more accurate valuation of the underlying contract. Our model assume an efficient market in that all carrying costs of the underlying good are accounted for in the futures price of the commodity. Knowing the futures price and the spot price of oil, one might calculate the cost-of-carry (CoC) at t and model the volatility as a percentage. Forecasting the volatility of CoC more accurately could facilitate improved performance in various forms of arbitrage.

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