8th International Scientific Conference
"Business and Management 2014"
May 15–16, 2014, Vilnius, LITHUANIA
Section: Finance Engineering
*http://www.bm.vgtu.lt*

ISSN print 2029-4441 / ISSN online 2029-929X
ISBN print 978-609-457-650-8 / ISBN online 978-609-457-649-2
Article number: bm.2014.026
http://dx.doi.org/10.3846/bm.2014.026


# MODELLING CONDITIONAL VOLATILITY IN STOCK INDICES: A COMPARISON OF THE ARMA-EGARCH MODEL VERSUS NEURONAL NETWORK BACKPROPAGATION

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**Abstract.** The analysis of conditional volatility is a key factor to correctly assess the risk of several financial assets such as shares, bonds or index as well as derivatives (futures and options). The econometric models from the GARCH family are traditionally the most widely used to predict conditional volatility. As an alternative to the econometric models, neural networks can be employed to this end. This paper compares the econometric model ARMA-EGARCH with the neuronal network Backpropagation. Both methodologies have been applied on diverse international stock indices. The main conclusion to be stressed is that the neuronal network can significantly better predict conditional volatility than the econometric model.

**Keywords:** Conditional volatility, GARCH, Backpropagation neuronal network, stock index, prediction.

**JEL classification:** C01, C58, G17.

## 1. Introduction

The analysis of conditional volatility is necessary for the correct valuation of the risk incurred in investments in shares, bonds, indices and other financial assets like derivatives. A good prediction of the conditional volatility is a key factor, for example, when diversifying portfolios, valuing financial options, applying risk measures like the VaR etc. This is the reason why it is so important to generate models able to accurately predict volatility.

Currently, the econometric models from the GARCH family are the most widely employed to predict conditional volatility (Teresiene 2009; Aktan *et al*. 2010; Tampakoudis *et al*. 2012; Zakaria and Winker 2012).

Nevertheless, recent studies are not applying econometric models but artificial intelligence techniques like neuronal networks to analyze financial markets (Maknickiene *et al.* 2013; Maknickiene 2012; Maknickiene *et al.* 2011; Rutkauskas *et al.* 2010). Furthermore, several studies show that neuronal networks, in particular the Backpropagation Neuronal Network (BNN) can be an alternative to predict conditional volatility (Wang *et al.* 2011; Aldin *et al*. 2012; Dzikevicius and Stabuzyte 2012).

In this work we will compare the predictive power of the econometric model and the neuronal network to forecast conditional volatility. To this end, the conditional volatility in several stock indices is predicted by means of a model belonging to the ARMA-EGARCH family, which is an econometric model widely used in the literature to forecast stock returns and conditional volatility (Rastoji 2012; Rachev *et al.* 2007; Tang *et al.* 2003) and by BNN. The research undertaken will show that, in general, the results obtained by the BNN are more accurate than those by the econometric model. The study has been applied to different international stock indices with different sizes and belonging to different geographical areas, with daily, weekly and monthly data.

The results obtained in our research are in line with other similar studies that show the capability of BNN to beat the traditional econometric models. For example, Yim (2002) analyzes the daily volatility of the BOVESPA index. Hossain *et al.* (2010) verify similar results applying the neuronal networks and econometric models to the foreign Exchange rates USD/JPY y USD/GBP. More recently, Lahmiri (2012) studies the conditional volatility of the stock indices in Morocco and Saudi Arabia using an ARMA-EGARCH model and BNN, obtaining similar results than in our study. The contribution of our research is that we make the comparison of the two techniques employing a robust database covering a complete economic cycle. The database includes daily, weekly and monthly data from five international stock indices with different size and structure belonging to different economic areas. Furthermore, the comparison has been made using the same variables both in the econometric model and in BNN. This is not the case in previous studies in which more variables are used in BNN, so the results obtained are not really comparable.

## 2. Comparison of the econometric ARMA-EGARCH model and the neuronal network BNN

The exponential GARCH model (EGARCH) introduced by Nelson (1990) captures asymmetric shocks of the conditional variance to past residuals (innovations). The general GARCH model (Bollerslev 1986; Engle 1982) and other asymmetric models require the use of non-negativity restrictions in many of the parameters to guarantee the positive sign of the conditional variance. These restrictions are not necessary in the EGARCH model as the positive sign of the conditional variance is guaranteed by the logarithmic function that follows:

$$\log(h_t) = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \left[ \gamma \frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}} + \left( \frac{|\varepsilon_{t-j}|}{\sqrt{h_{t-j}}} - (2/\pi)^{1/2} \right) \right], \quad (1)$$

where:

$\gamma$ captures the asymmetry of the conditional volatility. Generally this parameter will be negative. Therefore positive shocks in the performance will generate less volatility than negative shocks or negative innovations

$p$ and $q$ are the lags of the EGARCH ($p$,$q$) model

The present paper compares the EGARCH model with the neural network BNN (Rumelhart *et al.* 1986). This network employs supervised learning based on the delta rule and it learns though backward propagation mechanism. The BNN has got an input layer, an output layer and at least one hidden layer. The operation process of BNN is structured in two phases. First, the information enters the neurons in the first layer (input layer) and generates pair-wise associations of input –output data. Second, the information flows through neurons in the next layers and a comparison is made of the outputs obtained by the neuronal network and the desired output. The error made during the learning process is then calculated.

The errors of each neuron are transmitted backwards from the neurons in the output layer towards the neurons in the previous layers in order to determine the contribution of each neuron to the total error. Having this new information, the weights of the neurons are modified to reduce the error made until a defined minimum threshold is achieved or until the supervisor manually stops the learning process.

The learning algorithm of the generalized delta rule is expressed as follows:

$$\Delta w_{ij}(t+1) = \alpha \delta_{pj} y_{pi} + \beta \Delta w_{ij}(t), \quad (2)$$

where:

$\alpha$ – is the learning factor that will have a value between 0 and 1. This parameter determines the learning speed of the neuron and its value will remain constant

$y_{pi}$ – is the output value of neuron $i$ under the learning pattern $p$

$\delta_{pj}$ – is the value of delta or the difference between the desired output value and the value actually obtained by the neuronal network

$\beta$ – is a constant that determines the effect in $t+1$ of the change in the weights in time $t$. With this constant a better convergence is achieved with less iterations.

The implementation of the Backpropagation algorithm or generalized delta rule imposes the use of neurons with a continuous and differentiable activation function. This function is normally sigmoid or tan-sigmoid, but linear functions can also be used.

One of the common criticisms made at neuronal networks is that they are similar to a “black box” (Benitez *et al.* 1997) that is, they may be able to make a good prediction but is very difficult to understand the resulting model, the internal process that takes part inside the neuronal network, in the hidden layers. The main argument is that in the traditional econometric models it is easier to obtain a clear relationship between the variables employed and this is not the case in neuronal networks.

## 3. Prediction of conditional volatility in stock indices: ARMA-EGARCH vs. BNN

For this study five international stock indices have been selected with different size and different structure. The selected indices are the following: DAX (Germany), IBEX-35 (Spain), NIKKEI-225 (Japan), NASDAQ-100 (USA) and S&P-500 (USA). For all these indices daily, weekly and monthly performance data have been obtained in order to analyze whether the comparison of the econometric model and the neuronal network is robust across data with different frequency.

The observation period (sample period) for all the indices lasts from the beginning of 2000 until the end of 2010. Five estimation and prediction samples have been generated. A period of six years is always used for the estimation of the prediction model and the next year is used to make the prediction, as shown on Table 1:

**Table 1.** Periods for estimation and prediction (source: compiled by authors).

| | Estimation | Prediction |
|---|---|---|
| 1 | 2000-2005 | 2006 |
| 2 | 2001-2006 | 2007 |
| 3 | 2002-2007 | 2008 |
| 4 | 2003-2008 | 2009 |
| 5 | 2004-2009 | 2010 |

As can be observed, the first year of the estimation period has been shift forward by one year to obtain the five periods. The objective is to verify that the results obtained are consistent over time. Some studies confirm the need to calculate the estimations and the predictions with different shifted observation periods (Fries *et al.* 2013; Pozo *et al*. 2013)

In order to compare the predictive power of the econometric model and the neuronal network the errors made by each model for every sample are calculated. Four different types of prediction error measures have been calculated: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Percentage Error (MPE) and Root Mean Square Error (RMSE). It has been considered that the neuronal network overcomes the econometric model when the prediction errors of BNN are smaller than those of the econometric model in all of the four error measures described.

### 3.1. Prediction of the conditional volatility in the ARMA-EGARCH model

First of all the stationarity of each of the data series is analyzed. To this end the augmented unit-root test by Dickey-Fuller (DFA) and the Phillips-Perron test are used (Dickey *et al.* 1984). The tests are applied without constant and without tendency; with constant; and with constant and with tendency. To calculate the lags to conduct the tests, the Schwartz criterion has been employed. The tests have been calculated with a level of significance of 1%, 5% y 10%. The non-existence of unitary roots confirms the stationarity of the series. All the data series with the daily, weekly and monthly performance, for all the indices are stationary as the statistical values reject the null hypothesis of the existence of unitary roots both using the DFA test as the Phillips-Perron test. The stationarity of the series is verified as well when making the tests without constant and without tendency, with constant and with constant and tendency.

Once the stationarity of the series has been verified, the analysis of the autocorrelation of the residuals is undertaken. To this end a regression with different lagged values, from one to five, is calculated for each of the series. The test employed is the Durbin's h statistic, for the null hypothesis that the errors are serially uncorrelated against the alternative that they follow a first-order autoregressive process. Furthermore, this test allows for the existence of lags in the dependent variable (index performance). After analyzing the daily, weekly and monthly data, it can be concluded that there is no first order autocorrelation of the residuals for the indices of our sample. Figure 1 shows, as an example, the results of the test applied on the daily performance of the German DAX index with five lags.

Dependent Variable: RT
Method: Least Squares
Date: 07/18/11 Time: 13:33
Sample (adjusted): 7 2786
Included observations: 2780 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 2.58E-06 | 0.000310 | 0.008314 | 0.9934 |
| RT(-1) | -0.037216 | 0.018955 | -1.963361 | 0.0497 |
| RT(-2) | -0.022036 | 0.018923 | -1.164521 | 0.2443 |
| RT(-3) | -0.024497 | 0.018921 | -1.294724 | 0.1955 |
| RT(-4) | 0.045771 | 0.018921 | 2.419006 | 0.0156 |
| RT(-5) | -0.054589 | 0.018921 | -2.885036 | 0.0039 |

| | | | |
|---|---|---|---|
| R-squared | 0.007916 | Mean dependent var | 1.20E-06 |
| Adjusted R-squared | 0.006127 | S.D. dependent var | 0.016395 |
| S.E. of regression | 0.016344 | Akaike info criterion | -5.387725 |
| Sum squared resid | 0.741031 | Schwarz criterion | -5.374926 |
| Log likelihood | 7494.938 | Hannan-Quinn criter. | -5.383104 |
| F-statistic | 4.426572 | Durbin-Watson stat | 2.001930 |
| Prob(F-statistic) | 0.000511 | | |

**Fig. 1.** Durbin's h test. DAX with daily data (source: compiled by authors)

Nevertheless, Durbin's h statistic is only capable to detect first-order autocorrelation. To detect the presence of higher order serial autocorrelation the Breusch-Godfrey test has been applied (Breusch 1978; Godfrey 1978). The autocorrelation of residuals up to lag five were calculated for all the indices and for all data frequencies. The same conclusion of no autocorrelation was obtained.

Different ARMA models with different lag orders both in the autoregressive part as and the moving average part of the model have been estimated. That model has been selected with the best performance according to the Schwartz information criterion.

In must be underlined that the non-existence of autocorrelation in the residuals simply means that there is no linear relationship between the residuals and their lags; nevertheless, a different case of relationship, for example an exponential relationship, could exist.

To assess the existence of heteroskedasticity in the residuals, that is, to analyze whether there are or not autoregressive conditional heteroskedasticity (ARCH) processes in the residuals, it is necessary to conduct a specific test, the ARCH test. We make this test using the same level of significance for all the indices and for all the frequencies. For all the cases a value higher than the critical value was obtained, so the null hypothesis of non-heteroskedasticity can be rejected and its existence is confirmed for all the series in the sample. Figure 2 shows the results obtained on the DAX index daily data.

Heteroskedasticity Test: ARCH

| | | | |
|---|---|---|---|
| F-statistic | 2.784105 | Prob. F(5,2772) | 0.0163 |
| Obs*R-squared | 13.88095 | Prob. Chi-Square(5) | 0.0164 |

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 07/18/11 Time: 13:46
Sample (adjusted): 9 2786
Included observations: 2778 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 1.016654 | 0.053279 | 19.08179 | 0.0000 |
| WGT_RESID^2(-1) | -0.064840 | 0.018991 | -3.414241 | 0.0006 |
| WGT_RESID^2(-2) | 0.001339 | 0.019031 | 0.070370 | 0.9439 |
| WGT_RESID^2(-3) | 0.021387 | 0.019028 | 1.123997 | 0.2611 |
| WGT_RESID^2(-4) | 0.007226 | 0.019033 | 0.379665 | 0.7042 |
| WGT_RESID^2(-5) | 0.018641 | 0.018995 | 0.981370 | 0.3265 |

| | | | |
|---|---|---|---|
| R-squared | 0.004997 | Mean dependent var | 1.000431 |
| Adjusted R-squared | 0.003202 | S.D. dependent var | 1.570014 |
| S.E. of regression | 1.567499 | Akaike info criterion | 3.738997 |
| Sum squared resid | 6810.949 | Schwarz criterion | 3.751804 |
| Log likelihood | -5187.467 | Hannan-Quinn criter. | 3.743622 |
| F-statistic | 2.784105 | Durbin-Watson stat | 2.000091 |
| Prob(F-statistic) | 0.016302 | | |

**Fig. 2.** ARCH Test. DAX with daily data (source: compiled by authors).

Some authors (Ferreira *et al*. 2008; Liu *et al*. 2010; Wang *et al*. 2012; Bentes *et al*. 2013) verify the existence of asymmetries in the volatility of the S&P 500, FTSE 100, DAX 30, CAC 40, IBEX 35 and other indices which can be captured by econometric models like the EGARCH model. For this reason, the estimation of the EGARCH model was calculated for different time lags, where the Schwartz criterion was used to select the most suitable lag. Table 2 shows the selected models for the different indices with daily, weekly and monthly data.

**Table 2.** Selected ARMA-EGARCH model (source: compiled by authors)

| INDEX | DAY | WEEKLY | MONTHLY |
|---|---|---|---|
| DAX | ARMA(2,2)-EGARCH(1,1) | ARMA(1,1)-EGARCH(1,1) | ARMA(2,2)-EGARCH(0,1) |
| IBEX-35 | ARMA(2,2)-EGARCH(1,1) | ARMA(1,1)-EGARCH(1,1) | ARMA(1,1)-EGARCH(0,1) |
| NASDAQ-100 | AR(2)-EGARCH(1,1) | ARMA(2,2)-EGARCH(1,1) | ARMA(2,2)-EGARCH(0,1) |
| NIKKEI-225 | ARMA(1,1)-EGARCH(1,1) | ARMA(1,1)-EGARCH(1,1) | ARMA(1,1)-EGARCH(0,1) |
| S&P-500 | AR(2)-EGARCH(1,1) | ARMA(1,1)-EGARCH(1,1) | ARMA(1,1)-EGARCH(0,1) |

Next the estimation and prediction for each of the periods was calculated. Table 3 shows the error prediction of the ARMA-EGARCH model on DAX daily data by means of four different error measures.

**Table 3.** Different measures of error prediction. ARMA-EGARCH models. DAX with daily data (source: compiled by authors).

| PREDICTION YEAR | MAPE | MAE | MPE | RMSE |
|---|---|---|---|---|
| 2006 | 0.06034403 | 4.8329E-06 | 0.05534469 | 0.00219839 |
| 2007 | 0.04241025 | 3.5133E-06 | 0.02980572 | 0.00187437 |
| 2008 | 0.0715325 | 2.1584E-05 | -0.06712036 | 0.00464588 |
| 2009 | 0.14649749 | 4.1419E-05 | 0.14649749 | 0.00643578 |
| 2010 | 0.14920134 | 1.4917E-05 | -0.14885857 | 0.00386227 |

First of all, it must be stated that we have observed that the prediction errors in the econometric models have increased as the frequency of the data decreases, that is, the errors of the econometric models are bigger for weekly data than for daily data, and for monthly data than for weekly data. So the smaller the number of available data, the bigger the prediction errors.

Second, we have analyzed whether there is a relationship between the observed volatility in each period sample and the prediction errors. The aim is to determine if there are significative changes in the prediction errors between the different periods analyzed in function of the volatility observed. To make this analysis, the mean volatility for each period, index and data frequency has been calculated to determine in each of the periods if the period volatility increases or decreases and to compare the evolution of the prediction errors. No such relationship was observed, so the prediction errors are independent of the higher or lower volatility in the period analyzed.

### 3.2. Conditional volatility prediction by means of the Backpropagation neuronal network (BNN)

The Backpropagation Neuronal Network (BNN) has been used to calculate predictions of the conditional volatility of the fives indices, timeframes and subsample periods. This neuronal network has been chosen for its capacity to adapt the weights of the neurons to the errors done during the learning process. This is a key characteristic in order to obtain good results even in situations relatively different to those used in the learning period. The learning process of BNN is a supervised learning one, and it learns through backward propagation mechanism. In the training process BNN must receive the input values as well as the desired output values. The training process involves calculation of input and output values, activation and target functions, backward propagation of the associated error, and adjustment of weight and biases.

Two hidden layers have been used in the network. Multiple connections between the neurons have been permitted. Because of software limitation reasons, the maximum number of neurons in each layer has been limited to 256. Regarding the learning ratio for the two hidden layers, it has been changed randomly in different trainings and indices. So, in some cases learning ratios have been used that range from 0.1 to 0.4. In other cases the learning ratios varied from 0.1 to 0.7 and finally the ratios ranged between 0.1 and 0.3.

For the output layers, the learning ratios used have been 0.1 to 1, 0.1 to 0.5 and 0.1 to 0.3. The momentum parameter has been established between 0.1 and 0.3 or between 0.1 and 0.5. The initial weights of the neurons' connections have been set at +/- 0.3 or +/- 1.0 in different trainings. We have allowed the neuronal network to use different transfer functions. So, linear functions, sigmoid logistic functions and tan-sigmoid hyperbolic functions have been used.

In order to make a more accurate comparison between BNN and the econometric models, the same variables have been selected as input data of the neuronal network as those used in the econometric ARMA-EGARCH models. In the learning process, as the output values, the observed conditional volatility of the performance of the indices has been used.

One of the results obtained in this research is that those BNN that use the different transfer functions in a balanced way generally outperform the predictions of the econometric model. That is, the 255 neurons are homogenously divided in three groups, and each of the groups applies a different transfer function: 85 neurons have a linear transfer function, 85 neurons a logarithmic function and 85 neurons a tan-sigmoid one.

Table 4 shows the error prediction of BNN on DAX daily data by means of four different error measures. The results can be compared with those present on Table 3: The error predictions made by BNN are always smaller than those by the econometric model.

**Table 4.** Different measures of error prediction. Backpropagation Neuronal Network. DAX with daily data (source: compiled by authors).

| PREDICTION YEAR | MAPE | MAE | MPE | RMSE |
|---|---|---|---|---|
| 2006 | 0.05276384 | 3.5678E-06 | -0.02200645 | 0.00188886 |
| 2007 | 0.03709813 | 3.1921E-06 | -0.01135457 | 0.00178664 |
| 2008 | 0.03063524 | 1.6851E-05 | -0.00071188 | 0.00410501 |
| 2009 | 0.0219346 | 6.6893E-06 | 0.0096265 | 0.00258636 |
| 2010 | 0.04409063 | 6.34322E-06 | 0.00446736 | 0.00253618 |

As already was observed for the econometric model, the prediction error increases as the data frequency decreases, that is, the error is the highest with monthly data, where the number of available data is the smallest, and decreases with weekly and daily data, as the amount of available data grows. Nevertheless, the errors observed when using BNN are smaller than those observed in the econometric model. Therefore it seems obvious that neuronal networks can improve their generalization power and make therefore better predictions which are less influenced by the frequency of the data.

During the training process, the first network has been chosen which outperforms the results obtained by the econometric model using the four error measurement options mentioned above (MAPE, MAE, MPE and RMSE). Once the econometric model was outperformed by BNN, the training process was interrupted. Out of the 75 timeframes predicted (five timeframes for each of the indices multiplied by three – daily, weekly and monthly data) only in 6 cases BNN has not beaten the neuronal model in one or more error types. That is, only 8% of the neuronal networks have not been able to beat the econometric model (Table 5).

**Table 5.** Prediction errors: Neuronal Network BNN vs. ARMA-EGARCH model (source: compiled by authors)

| | | MAPE | MAE | MPE | RMSE |
|---|---|---|---|---|---|
| DAX (m) | V1 | 0 | 1 | 0 | 1 |
| IBEX (d) | V5 | 1 | 1 | 0 | 1 |
| NASDAQ(d) | V5 | 1 | 1 | 0 | 1 |
| NIKKEI (d) | V5 | 0 | 0 | 0 | 0 |
| NIKKEI (s) | V5 | 0 | 0 | 1 | 0 |
| S&P (d) | V1 | 0 | 0 | 1 | 0 |

1: BNN outperforms the ARMA-EGARCH model
0: ARMA-EGARCH model outperforms BNN

The best prediction results obtained by the neuronal network compared with the econometric model are not due to the overtraning of BNN. In fact, when applying BNN, two different periods have been used: one period for the training process and a different period to test the obtained network. This last period is the one employed for the comparison between BNN and the ARMA-EGARCH model.

## 4. Conclusions

In the last decades a wide body of research has been devoted to the prediction of financial asset price volatility. This is due to the key role played by volatility in portfolio management, valuation of financial options, investment decisions, VaR calculation and risk management in general.

Models form the GARCH family have been usually employed to predict volatility, but in recent times other techniques are competing with these econometric models. One of these techniques is the neuronal network.

In this study we have compared the prediction power of an ARMA-EGARCH model with a Backpropagation Neuronal Network on a dataset including five international stock indices with daily, weekly and monthly data. The aim is to test whether the neuronal network can beat the econometric model in all indices, in all prediction periods and regardless the data frequency. To compare the predictive power of both methodologies four different types of prediction error measures have been calculated. Furthermore, the variables employed in the econometric model and BNN have been the same in order to undertake a realistic comparison.

The results obtained in this research make it evident that the Backpropagation Neuronal Network outperforms the traditional econometric models in the prediction of conditional volatility regardless the frequency of the data.

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