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# Are option markets efficient?
# Volatility forecasting on the S&P 500-index option market with an EGARCH-Artificial Neural Network hybrid model

*A straddle-based trading perspective*

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# Introduction

Since the 1970's derivatives and in particular options play a crucial role in the financial markets and in the world economy, given their extensive usage for hedging, portfolio allocation, risk management and diversification purposes (Chance, 2004). In 2014 the total number of options traded worldwide exceeded 21,87 billion contracts, out of which almost 11 billion contracts were on equity or equity index (FIA, 2015). The options for S&P 500, one of the most significant indexes of the NASDAQ are traded on the Chicago Board Options Exchange (CBOE). The underlying S&P 500 index consisting the stocks of the 500 biggest national firm acts as an indicator of the whole US economy.

Forecasting the future price or the directional change of financial assets have always been in the frontline of economics and other applied sciences due to the potential economic gain from producing reliable estimates for future values of such assets. Since the 1970's and the formulation of Efficient Market Theory it is assumed that no extra profits are achievable, given that all information is incorporated in prices observed in the market. Consequently one cannot achieve abnormal gains by using the predictions of even the most sophisticated forecasting methods in trading. Although studies have shown several examples when temporarily inefficiencies in hands with abnormal gains occurred one cannot establish a successful trading strategy on the forecast of any methods on the long run (Timmermann & Granger, 2004).

Building a forecasting model on the options market differs from doing the same on the stock market. Not only the value of an option is highly dependent on the volatility of the underlying, but also the change in the level of the volatility affects a multitude of options with different strike prices and maturities. From a practical point of view, while forecasting stock prices means giving a firm estimate to "the" future price of the asset and is considered a one-dimensional problem, forecasting option prices is a multidimensional problem. Options with different exercise prices and maturities have different levels of volatility, thus their price cannot be modeled nor forecasted by one single tool. Therefore, by providing an accurate forecast on the volatility on a specific option one can theoretically gain abnormal returns with a trading strategy, as long as the prediction models the implied volatility of the option in question. The neural networks are suspected to give such reliable and accurate forecast due to their ability to capture nonlinear, noisy and nonstacionary effects in the structure of volatility. A great number of researchers have forecasted the volatility of the S&P 500 using various data mining models in diverse economic environments (Donaldson et al, 1996; Malliaris et al, 1996; Hamid et al, 2004; Hajizedah et al, 2012). Accurate forecasts could not only be achieved by using complex and hybridized models, but also by applying an ANN with the simplest structure. Research conducted on the field has verified the observation that future volatility is indeed predictable. However as many have pointed out forecasting with low measurement error is not the appropriate test of economic reliability of a model (Black & Scholes, 1972; Noh& Engle& Kane, 1997; Sheu & Wei, 2011). One must feed the forecast into a trading strategy and examine whether abnormal profits are achieved, or in other words concentrate on the economic not the statistic significance.

In this article we are trying to forecast the volatility of S&P 500 and prove the economic significance of the results by following the procedure detailed below. First we are producing an accurate forecast of the implied volatility of S&P 500 options by using a neural network enhanced with additional input variables. Secondly we feed the forecasted value to a the Option Trading Module to decide whether pricing anomalies do occur in different segments of the option market using call and put options with different time to maturities. Thirdly should an anomaly arise we long or short a straddle composed of a call and put option with similar exercise price and time to maturity parameters and hold it during a day from $day_t$ to $day_{t+1.}$ In the end of each period we summarize the profits gained by the strategy and examine whether abnormal profits were reached in the presence of adequate transaction cost. We are trying to find answers for the following three hypotheses described below:

**Hypothesis 1.)** The Artificial Neural Network provides a more accurate forecast of volatility than the GARCH model.

**Hypothesis 2.)** Abnormal profits can be gained by feeding the forecasted future volatility into a trading strategy even after taking transaction costs into account.

**Hypothesis 3.)** Options with different time to maturity react differently to the forecast of volatility, thus the level of profitability achieved differs in every segment of the option market. Studies in multiple segments of the option market have not been conducted from this aspect yet, so this paper aims to be a pioneer in connecting economic profitability with forecasting accuracy on multiple segments of the option market.

Furthermore synthesizing the second a third assumption we conclude that at any given underlying and period there is at least one segment of the option market, options with similar maturities where the Efficient Market Hypothesis does not hold.

Having introduced the topic and the main hypothesis of the research the remaining sections of this article are organized as follows. Section 1 presents the Efficient Market hypothesis and its application to stock and index price forecasting and volatility forecasting. The section also details the three methods generally applied in the literature determining whether option markets are efficient, and further elaborates on the connection between option pricing and volatility forecasting. Section 2 elaborates on the topic on volatility forecasting and different volatility models following the definition of volatility and the description of stylized facts in financial time series. This section further presents the neural networks and justifies their use in volatility forecasting. Section 3 introduces option-pricing techniques with special attention to the assumptions and shortcomings of the Black-Scholes model. This section further details the use of neural networks in option pricing making a distinction between those acting as quasi option pricing models and those merely using the proceeds of neural networks as inputs. Section 4 accounts for different methods of volatility trading emphasizing the importance of testing forecasting accuracy with trading strategies. After analyzing the delta neutral and straddle-based option trading strategy, the section concludes with the presentation of past research on option trading relying on volatility forecasts of neural networks.

In the second part section 5 gives an overview on the multicomponent model applied for volatility forecasting in the article, while section 6 details the data set used and the data preprocessing performed. The estimation and fitting of EGARCH(1,1) is also described in this section. Section 7 presents the mechanism of the model, by first describing the Volatility Forecasting and Option Trading Module and by walking the reader through the process from fitting and forecasting with the neural network to calculating the profit from the trading strategy. Section 8 presents the results of the research and benchmarks the result of the model to those of the GARCH model based trading. Section 9 concludes the paper and evaluates the hypothesis, sets the limitations of the research and defines the direction of future research.

## 1. Efficient Market Hypothesis and forecasting

According to the Eugene Fama a market in which prices always "fully reflect" available information is called efficient (Fama, 1970). In his work the scholar defines the three levels of market efficiency: the weak, the semi-strong and strong form. The weak form means that prices already reflect all the information incorporated in historic prices. The semi strong form suggests that prices efficiently adjust to other publicly available information, such as the announcement of periodical earnings, stock splits, dividends and related M&A activity. Finally the strong form of efficiency holds that all information "builds in" to the prices even those in the monopolistic possession of investor groups and participants. Jones and Netter propose a straightforward base for the distinction between the three forms of market efficiency. The weak form precludes only technical analysis from being profitable; while semi-strong extends it to both technical and fundamental analysis and the strong form means that even those with privileged information cannot achieve abnormal return (Jones et al, 2008).

Although many have criticized the theory both on theoretical and empirical grounds vast number of studies have been conducted on field. According to Fama (1970) if markets are weekly efficient the dynamics of an asset follow a random walk with a drift. As the process consists of two non-stationary components, the deterministic and the stochastic trend, the shocks affect stock prices through the latter. However should stock prices follow a trend stationary (mean-reversion) process one can forecast future prices from past behavior of an asset and earn abnormal returns by building a successful trading strategy on the anomaly (Lee et al, 2009). Inconclusive results have been produced by testing the unit root behavior of stock indices and individual stocks with univariate unit root test with or without breaks (Choudry, 1997; Kawakastsu et al, 1999; Chadhuri et al, 2003; Lee et al, 2003; Narayan, 2005; Qian et al., 2008). Furthermore panel unit root tests were applied to financial time series reaching a conclusion with similar results than those of the univariate tests (Chaudri et al., 2004; Narayan et al. 2005 & 2007; Lean et al, 2007). Although many studies have concluded that stock prices are characterized as a unit-root/ random walk these results are not robust and research with contradictory results left this issue as a still unanswered question in economics.

Forecasting volatility on the other hand has a vast literature where forecast was performed with a large variety of models such as parametric, non-parametric and machine learning techniques. One can build volatility models based on historic standard deviations (Random walk models, moving averages, ARIMA, ARFIMA models) or stochastic volatility, using implied volatilities derived from option prices, using on wide range models of the ARCH-GARCH family and non parametric, machine learning based models (Poon & Granger, 2003). Each approach listed above delivers a different estimate of volatility, as the '"true" conditional volatility is unobservable. Based on the definition of conditional variance one cannot simply specify the true conditioning information denoted by $\mathrm{E}(.\,|\Omega_{t-1})$ in the equation below:

$$\mathrm{E}\left[\left(r_t - \mathrm{E}(r_t|\Omega_{t-1})\right)^2 \middle| \Omega_{t-1}\right]$$

, where $r_t$ is the asset return realized at time t, $\mathrm{E}(.\,|\Omega_{t-1})$is the expectation conditioned upon the true information set Ω available at time t-1. Not only it is not known what is exactly the conditioning information, but also it is unclear whether the volatility estimated with information subset Ω is close to the true conditional volatility (Harvey & Whaley, 1992).

However one must take into consideration that even if market inefficiencies are found and arbitrated with a successful trading strategy it is highly unlikely that the anomaly will persist for a long period of time. Stable forecasting methods have a self-destructing mechanism when discovered and applied by large amount of investors. Not only does the specification of the model has to be recalibrated from time to time due to the non-stationary of time series, but also one must take into account the change in the level of transaction cost, undermining even the most refined forecasting results by diminishing trading profits significantly (Timmermann & Granger, 2004).

Pricing options and determining whether option markets are efficient is an intriguing and more complex issue than testing efficiency on stock markets. Several studies have been conducted on the field since the 1970's. Arising opportunities of arbitrage observed in the market are clear indications of inefficiency (Klemkosky and Resnick, 1979). There are three different approaches to detect such inefficiencies in the market and to observe the violation of the law of one price (Prykhodko, 2013).

The most straightforward way to detect inefficiency is to test the put-call parity, and other conversions between the price of the call and put option of the same underlying. This approach calculates the theoretical price of the put option by the parity and compares it's the observed market price. Should the put be overpriced (underpriced) investors short (long) the derivative, take an opposite position in the underlying and in the call option as well. Since the 1970's many scholars have conducted research on the topic and most of the result showed that even though violations of certain parities such as the box spread occur it does not necessarily lead to inefficiency (Phillips et al., 1980; Billingsley & Chance, 1985; Chance, 1986; Chance, 1987; Ronn, 1989; Kamara & Miller, 1995; Ackert & Tian, 2001 ). One can also test the efficiency of the option market by comparing the observed option prices in the market to those calculated by an adequate option pricing model (Chaudhury, 1985). This approach relies on the fact that models capture the characteristic of the market differently and by choosing an adequate model one can estimate option prices more effectively (Galai, 1977; Hutchinson et al. 1997;Panayides, 2005; Panayiotis et al., 2008). The last and the most significant approach from our perspective is to test whether abnormal profits can be gained by giving an estimate to the future level of volatility and by applying it in trading. Contradictory conclusions have been reached by preceding research. According to some articles even tough anomalies do occur, as soon as transaction costs are taken into account extra profit diminishes rapidly and the market remains efficient (Chiras & Manaster, 1978; Harvey & Whaley, 1992; Guo, 2000). Others have reached opposite conclusion and even after accounting for an adequate amount of transaction cost, abnormal level of profits remained on the market, thus making it inefficient (Chiras & Manaster, 1978; Engle et al., 1993; Bartels & Lu, 2000; Sheu & Wei, 2011; Quek & Tung, 2011).

However finding published articles on such anomalies, which are persistent and can be exploited by the implementation of a trading strategy, is almost impossible for three reasons. Firstly stable forecasting methods are unlikely to exist for long periods of time, because as soon as they are discovered by a large number of investors they will cease to exist, thus making any market efficient at least on the long run. Secondly as Guo has pointed out even discovering of a model able to forecast with the highest precision does not necessarily mean that the market in question is inefficient (Guo, 2000). In the presence of adequate transaction costs the extra profit seemingly realized from forecast might erode, thus undermining the validity of the model. Finally as published scientific papers attempting to forecast returns seem to produce inconclusive results we might suspect that the reverse file drawer bias is present. In other fields of economics the "file drawer effect" means that studies finding insignificant effects are difficult to publish, therefore they are more likely to end up under a huge the stash of paper on the desk of the researcher, hence the name. However in case of studies on market efficiency the effect is reversed, as a researcher finding a successful model is more likely to sell it to an investment bank than to publish it in an academic journal (Timmermann & Granger, 2004).

# 2. Volatility modeling and forecasting

## 2.1 The motivation of volatility forecasting

In finance volatility is defined as the standard deviation of return provided by the variable per unit of time when the return is expressed using continuous compounding (Hull, 2015). It can also be regarded as a measure of fluctuation in a financial security price around its expected value (Rajashree et al., 2015). Forecasting volatility and establishing volatility models that produce reasonable estimates for future volatility play a key role in achieving economic gain from various financial applications. According to Reider (2009) the three main purposes of forecasting volatility are risk management, asset allocation, and taking bets on future volatility. The main goal of risk management is to measure the potential losses arising from various sources, while giving an accurate estimate of the future volatilities and correlations between the factors. Asset allocation aims to define the optimal allocation of assets in a large portfolio applying the Markowitzian approach of minimizing risk for a given level of expected returns. In order to find the optimal allocation one not only needs to forecast the future volatility, but also estimate the variance-covariance matrix of all assets in the portfolio (Reider, 2009). The last and most interesting application of volatility forecast is to use it in a trading strategy of volatility dependent financial assets, such as options, futures and other derivatives.

In the literature volatility forecasting models are generally classified in four categories: Historical or realized volatility models, the options implied standard deviation model, the ARCH-GARCH family models, and the stochastic volatility model (Blair at al, 2001; Poon & Granger, 2003). In the following section we will summarize the stylized facts of financial time series, briefly presenting the abovementioned models and detail the applied forecasting methods.

## 2.2 Stylized facts of financial time series and volatility

Financial time series exhibit several empirical patters that play an important role in specifying, estimating and forecasting in a model. Out of the 12 stylized facts of the returns of financial time series, first summarized by Poon & Granger (2003) five relate to volatility: The fat tails, the volatility clustering, the leverage effect, the long memory and the co-movements in volatility. Fat tails refers to a specific aspect of the distribution of financial time series, exhibiting fatter tails than those of a normal distribution. This observation is also exhibited in excess kurtosis. While the standardized fourth moment for a normal distribution is 3 for many financial time series it is far above this value (Fama, 1963). For modeling excess kurtosis, distributions, which have fatter tails than the normal, such as the Pareto and Levy, have been proposed in the literature (Knight & Satchell, 2007). Another stylized fact is the clustering of periods of volatility, where large movements in volatility are followed by further large movements. Clustering of volatility, or in other words, persistence of shocks can be demonstrated by correlograms and Ljung-Box statistics. The leverage effect means that financial time series price movements are generally negatively correlated with volatility. Empirical evidence on leverage effects can be found in Nelson (1991), Gallant, Rossi and Tauchen (1992, 1993), Campbell and Kyle (1993) and Engle and Ng (1993). Another stylized fact called long memory, especially apparent in high-frequency data states that volatility is highly persistent and provides evidence of near unit root behavior in the conditional variance process. Capitalizing on this observation ARCH-GARCH family models have incorporated unit root behavior, while Stochastic Volatility models used the long memory process for modeling persistence. Lastly co-movements in volatility appear when financial time series are observed across different markets. Significant movements in one currency coinciding with that of another usually suggest the importance of multivariate models in modeling cross-correlations of different markets (Knight & Satchell, 2007). Although GARCH model family has shown promising sings of capturing certain aspects of stylized facts, most of the nonlinearity and stochastic effect of volatility were still left unaccounted for. Both stochastic volatility models and data mining techniques take these effects into account and the latters even provide a forecast for future values of the volatility without exploring and sticking to strict assumption, thus offering a more robust solution for the problem.

## 2.3 Historical volatility models

Historical volatility is the most straightforward way to quantify the deviation of a financial asset. The method, also called statistical volatility calculates the standard deviation of an asset over a fixed period of time, such as 30,60 or 90 days. Using the natural logarithm of closing prices between each interval of time historical volatility is calculated as follows.

$$HV=\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i-\bar{x})^2} \qquad \text{and} \quad x_i=\ln(\frac{P_i}{P_{i-1}})$$

,where X is the return at the end of the $i^{th}$ interval, Pi is the closing price of a stock at the end of the $i^{th}$ interval and n+1 is the number of observations or number of observed days for daily basis (Amornwattana et al., 2007). Historical volatility allows one to observe the movements of volatility by comparing volatility estimates for different time span. For example should the 30 days volatility be significantly greater than the one for 90 days an increase in the level of volatility in general is expected. Given that the historic or realized volatility is the most simple volatility model it serves as an input parameter to many time series and option pricing models (OPM) such as the Black Scholes model. Despite of the fact that it is easy to calculate and can be applied in the most straightforward way, the model has several drawbacks. Sudden changes in volatility are usually neglected and higher level of volatility at time t gets stuck in the model for long period of time, or in other words the model is persistent.

## 2.4 Implied volatility models

Implied volatility is the proxy for market expectations on the future volatility of an asset, or by definition it is the volatility of the market price of an option when it is substituted into the pricing model. Derived from parametric option pricing models, such as the Black Scholes formula this volatility measure accurately represent the volatility of a specific option with given time to maturity and exercise price. As opposed to realized volatility that reflects the volatility of an asset for the preceding period, implied volatility represent the expectations of investors concerning the near future it serves as a proxy to measure investor fear. Compared to the historical volatility, implied volatility has a specific pattern when observed for options with different strike price called volatility smile. The implied volatility can be modeled and forecasted by Implied

Volatility Stochastic Regression (Guo, 2001), by parametric models and data mining techniques such as neural networks. Several articles addresses the problem of finding the adequate option pricing model to capture the "true" implied volatility by comparing the results from different models (Engle, Kane, Noh, 1997; Roh, 2007; Bianconi et al., 2015). Others are searching for the adequate model for forecasting purposes and draw comparisons between different models (Koopman et al., 2004; Ahoniemi, 2008; Figlewski, 2004). The last two section presented both the implied and the historical volatility measures as adequate tools for forecasting, if however the research is conducted on the option market the former must be favored. Realized volatility with its looking back calculation method cannot grab the forward looking characteristics of the expected level of volatility built in to the option prices, thus proves to be an inefficient measure in option pricing.

### 2.5 ARCH-GARCH model family

Let $R_t$ be the return of a financial asset with conditional forecast $E(R_t|I_{t-1})$as in equation.

$$R_t = E(R_t|I_{t-1}) + \epsilon_t$$

, where $I_{t-1}$ is the conditional information set on which forecasts are based and the additive forecast error has zero mean and conditional variance.

$$E(\epsilon_t^2|I_{t-1}) + \epsilon_t^2$$

The flaw of classical time series models is that $\epsilon_t$ appears to be drawn from time dependent heteroscedastic distribution. Therefore the main goal of conditional volatility models are to capture this effect and produce a forecasted variance $(\breve{\sigma}_t^2)$, along with a return forecast error $(\breve{\epsilon}_t^2)$, so that the standardized residuals, $(\breve{\epsilon}_t^2/\breve{\sigma}_t^2)$ are homoscedastic and independent. The Autoregressive Conditional Heteroscedasticity (ARCH) model, originally proposed by Engle (1982) addresses this problem by creating a time series model where the variance is forecasted as a moving average of past error terms. The ARCH model consists of three equations and it models the unconditional variance with an AR (1) process.

$$y_t = c + \phi y_{t-1} + u_t$$
$$u_t = \sigma_t \epsilon_t \ \epsilon_t \sim I.I.D.(0,1)$$
$$\sigma_t^2 = a_0 + a_1 u_{t-1}^2$$

The introduction of the model inspired academics to search for more refined models to capture the structure of volatility inherent in financial time series. The GARCH model (Generalized ARCH), a generalized form of ARCH proposed by Bollerslev (1986) reflects nonlinear dependence of the conditional variance of the time series, estimating jointly a conditional mean and conditional variance equation (Rajashree et al., 2015).

$$y_t = c + \phi y_{t-1} + u_t$$

$$u_t = \sigma_t \epsilon_t \; \epsilon_t \sim I.I.D.(0,1)$$

$$\sigma_t^2 = a_0 + \sum_1^{t-1} a_1 u_{t-1}^2 + \sum_1^{t-1} b_1 \sigma_{t-1}^2$$

Even though the model readily captures the persistence of volatility it lacks the ability to appropriately address the effects of negative and positive information. Consequently should we need to produce estimates on an asymmetric market the forecasting power of the model would diminish rapidly.

The EGARCH (Exponential GARCH) model, proposed by Nelson (1991) responds to this flaw of the GARCH by specifying conditional variance in logarithmic form. Using the specification estimation constraints to avoid negative variance is no longer needed and the model captures the stylized fact easier that a negative shock leads to higher conditional variance than a positive shock. (Poon & Granger, 2003)

$$y_t = c + \phi y_{t-1} + u_t$$

$$u_t = \sigma_t \epsilon_t \; \epsilon_t \sim I.I.D.(0,1)$$

$$\ln \sigma_t^2 = w + \sum_{j=1}^{p} \beta_j \ln \sigma_{t-j}^2 + \sum_{i=1}^{q} \gamma_i \left[\!\left[ \frac{r_t - i}{\sigma_t - i} - \sqrt{2/\pi} \right]\!\right] + \sum_{i=1}^{q} \alpha_1 \frac{r_t - i}{\sigma_t - i}$$

Based on extensive research on the use of EGARCH model in forecasting volatility the model readily captures the otherwise overlooked asymmetry and provides an adequate tool for modeling on noisy markets (Donaldson & Kamstra, 1997; Roh, 2007; Tseng et al., 2008; Hajizedah et al., 2012). The papers listed above detail the use of forecasted volatility from the EGARCH model as inputs to neural networks and other data mining techniques. By feeding the model-based volatility into a neural network alongside other inputs we are bound to get smaller error measures and more accurate forecast results. Naturally the volatility model itself can be applied to financial time series as it produces quite accurate forecast for future volatility (Andersen & Bollerslev, 1998).

## 2.6 Data mining techniques & Neural Networks for forecasting volatility

### 2.6.1 Neural Network and data mining techniques

An Artificial Neural Network (ANN) is an information-processing nonparametric method generally used from the 1970's for function approximation and classification in various scientific and applied fields. As a branch of business intelligence (BI) data mining aims to discover hidden patterns in large set of data and further use them for various business purposes (Badics, 2014). Originally invented and used for engineering, mathematics and informatics data mining techniques were first introduced to the financial world in the 1980's and have been used for various financial application ever since. Given that financial time series are generally noisy, non-stationary, and consist nonlinearity, stochastic parameters and structural breaks giving an accurate forecast for their future value was a puzzling problem at that time (Hall, 1994; Li, et al., 2003; Huang et al., 2010; Lu et al., 2009). With the introduction of data mining techniques to finance, academics and practitioners quickly built on their main advantage, namely that they could easily forecast future results of various time series by learning the pattern of market variables while disregarding strict theoretical assumptions.

Artificial Neural Network (ANN) has several variants appearing in the literature on forecasting financial time series, but generally the Multi-Layer-Perceptron (MLP) model is used (Kaastra & Boyd, 1996). The MLP network normally has 3 or 4 layers, one or two hidden layer between the input and the output layer. The input layer has equivalent number of neurons as the number of input parameters to the model, while the number of neurons in the output layer corresponds to the target variable; one neuron is used for continuous, two for binary output modeling. The number of neurons in the hidden layer corresponds to the complexity of the model. *(Fig. 1.)* Additionally all layer except the target layer contain an extra neuron called the bias neuron, which acting similarly as an intercept in an ordinary least square regression has the value of one (Badics, 2014). Normally, each neuron in a given layer is connected to all the other neuron in the following layer. As each connection represents a weight factor, the information reaches a single hidden layer neuron as the weighted sum of its inputs (Sermpinis et al., 2012). Within each neuron the information input is processed with an activation function. There is a number of activation functions in use and in application according to the purpose of the network such as the step function, continuous log sigmoid, continuous tan sigmoid, softmax and hyperbolic tangent functions. For function approximation the hyperbolic tangent (tanh) function has been found to produce consistent results based on earlier research (Kriesel, 2007).

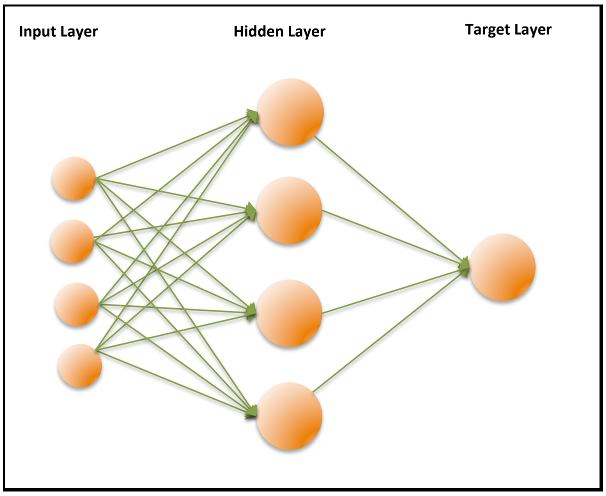


*Fig 1. Artificial Neural Network with a hidden layer (Source: own editing)*

The Artificial Neural Network has the ability to study complex relationships between variables and incorporate the nonlinearity and stochastic effects otherwise overlooked by traditional econometric models. Several studies have analyzed its ability to forecast stock or index prices (Chen et al., 2003; Chun & Kim, 2000; Thawornwong & Enke, 2004; Hansen & Nelson 2002) with positive results, just as it has been applied to forecasting the historic or implied volatility of financial time series (Donaldson et al, 1996; Roh, 2007; Kristjanpoller et al, 2014; Tseng et al, 2009, Monfared et al, 2014).

### 2.6.2 Forecasting volatility with Neural Networks

Neural networks, alongside with other data mining techniques have been proved successful in forecasting future value of volatility of financial time series'. Malliaris and Salchenberger wrote one of the earliest articles on neural networks predicting volatility. Using several exogenous and lagged variables they forecasted the implied volatility of S&P 100 index (OEX) using a sample of daily returns from 1992. The goodness-of-fit of the prediction, measured by MAD and MSE, as well as the high directional accuracy spurred others to develop and apply similar models. (Malliarias et al., 1996) Donaldson and Kamstra have proved that Artificial Neural networks can accurately capture the conditional variance of the otherwise unforeseeable component of returns. They have examined the time series of S&P 500, TSEC, NIKKEI and FTSE during 1970 to 1990 and found that ANN provides superior explanatory power compared to GARCH, EGARCH and GJR-GARCH models (Donaldson & Kamstra, 1997). Hamid and Iqbal forecasted the realized volatility of the S&P 500 index and then compared the results to the implied volatility derived from corresponding options by using Barone-Adhesi and Whaley option pricing method. The results show that forecasts from neural networks outperform those from implied volatility (Hamid & Iqbal, 2002).

Others applied an ANN hybridized with the outputs of other statistical an econometric model forecasts. Hybridization is a process, in which the beneficial features of several models are combined to form a new enhanced model in order to produce superior forecasting results. Roh (2007) used the forecast of the GARCH, EGARCH and EWMA models and fed them to ANNs beating the results of traditional methods in terms of error measures and goodness of fit. Hajizedah et al (2012) applied the forecasts of a GARCH and EGARCH models, but they also incorporated randomly generated time series using the parameters of the specified volatility models accounting for stochastic effects of volatility. The study performed on the S&P 500 index covered a decade from 1998 and showed an increased explanatory power, mainly due to the incorporation of generated time series model outputs to the model. Out of the vast amount of research on the subject outshines Kristjanpoller et al's (2013), who applied hybrid GARCH-ANN models to South American indices demonstrating an increased efficiency compared to traditional GARCH and ANN models. Finally Monafred and Enke (2014) have examined the performance of hybrid GARCH-ANN-s in different economic cycles and found that ANN outperforms traditional models in the periods of market turbulence, but might not prove as useful in calm periods.

There are several other data mining methods to forecast either stock index prices or volatility, such as the Support Vector Machine (SVM). SVM is a classification method designed to avoid the over fitting problem of neural network, which in turn is more likely to fall into local minima of the training error (Empirical Risk Minimization Principle). SVM minimizes structural risk, the upper bound of generalization error and thus handles high dimensional and noisy data better. There is an extensive literature on volatility forecasting with SVMs producing superior results compared to those of the classical econometric models'. (Andre et al., 2005; Gavrishchaka et al., 2006; Tang et al, 2009; Wang& Ping, 2011) Given the limited extent of this article the application of SVM to volatility forecast will only be put in practice in future research.

### 2.7 Measuring Goodness of fit of volatility models

In financial time series analysis the forecasting error is defined as the difference between the actual and the forecasted value of the time series. For evaluative purposes these errors are summarized and based on the mechanism of the error measure transformed. The six most common error measures in time series analysis are mean error, mean squared error, mean absolute error, mean percentage error and mean absolute error and root mean square absolute error. (Armstrong, 2001) Given that most of the studies have used MAE, MSE and RMSE as error measures, we are going to apply them as well (Ahoniemi, 2008; Panayotis et al., 2008; Roh, 2007). The equations of the listed error measures are as follows:

MAE: $\frac{1}{T}\sum_{t=1}^{T}|y_t - f_t| = \frac{1}{T}\sum_{t=1}^{T}|e_t|$

MSE: $\frac{1}{T}\sum_{t=1}^{T}(y_t - f_t)^2 = \frac{1}{T}\sum_{t=1}^{T}(e_t)^2$

RMSE: $\sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t - f_t)^2} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(e_t)^2}$

, where the t and T denotes the first and last observation of the time series of future values, $y_t$ stands for the realized and $f_t$ for the forecasted value of the time series at time t. Both MSE and RMSE provide an accurate tool for measuring forecasting error, but as the MATLAB applies the MSE as an error measures in the neural toolbox we further rely on this measure to compare the goodness-of-fit of different time series. However we must note that low MSE values and high accuracy is just a statistical test on the quality of the forecast, to check whether it is meaningful economically we must feed the results into a trading strategy.

# 3. Option pricing techniques

## 3.1 Parametric models benefits and drawbacks

An option is a traded security giving the right to buy or sell an asset, for fixed price (exercise price) within a specified period of time (American type) or on a specified future date (European type) (Black & Scholes, 1973). Before 1970, even though a few scholars have published articles on valuation formulas for options (Sprenkle, 1961; Ayres, 1963; Boness, 1964; Samuelson, 1965; Baumol et al., 1966 and Chen, 1970) traders calculated their fair price based on individual valuations, empirical observations and experience. Since its introduction in 1970, the Black-Scholes model is considered as one of the biggest successes of financial theory both in terms of approach and applicability (Teneng, 2011).

The model is based on the following assumptions: volatility and risk free interest rate are constant, stock price follows a random walk and pays no dividends, the option is European, there are no transaction costs and market is perfect. The price of a call option is denoted as follows:

$$C^{mdl}_{X,t,r,\sigma} = SN(d_1) - Xe^{-RT}N(d_2)$$

$$d_1 = \frac{\ln\left({}^{S}\!/_{X}\right) + \left(R + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}$$

$$d_2 = d_1 - \sigma\sqrt{T}$$

, where S is the current underlying price, X is the exercise price, T is the time to expiry, R is the interest rate and σ is the volatility of the underlying and $N(d_x)$ is the cumulative probability distribution function for the standard normal distribution. The equation provides a useful, relatively straightforward and well-formulated answer to the pricing of an option, providing that one accounts for the underlying assumption of the model framework.

However as many scholars have pointed out the model is built on some unrealistic assumptions about the market undermining its validity and ability to price options accurately. First of all the volatility in the model is depicted as constant over time. Although this observation might be accurate in short term, it is never so on the long term, as volatility varies stochastically over time (Poon et al., 2000). In addition, the so-called leverage effect, namely that volatility is negatively correlated with asset price return while trading volume produces co-movement with number of trades, undermines the theory of constant volatility (Nelson, 1991). All in all holding volatility constant affects option prices in such extent that it undermines the validity of the model. Secondly, the model readily assumes that returns of log normally distributed underlying stock prices follow the normal distribution. However it has been pointed out in the literature that asset returns have a finite variance and semi-heavy tails (Clark, 1973). Thirdly the model hypothesizes that stock movement follows a random walk, with stock price in time T being independent from its lagged value leaving out the impact of several economic factors from the analysis. In reality martingale representation theorem might not even hold as there may not be a single source of uncertainty defining the derivative and it's underlying (Teneng, 2011).

Furthermore several other assumptions of the Black Scholes model do not hold when applied to real world financial time series such as the concept of constant interest rate, the lack of dividends during option's life, the lack of commission and transaction costs, the exclusive applicability to European style options and the perfect liquidity of market (Teneng, 2011). However we are only focusing on the inconsistency of first two assumptions because of two reasons. First the assumptions listed above might be handled by applying various modifications of the Black-Scholes equation and other parametric option pricing models to option pricing (Hull & White, 1987; Heston, 1993). Secondly this article addresses the problem of forecasting volatility with a novel model, which takes into consideration the nonlinearity and stochastic effects in the structure of option prices. Therefore addressing all the flaws of the Black-Scholes option-pricing framework is out of the scope of this research.

### 3.2 Option pricing with neural networks

In the past 20 years several studies have looked at ability of Neural Networks and other machine learning methods to forecast an accurate price for options. There are two distinct ways of how neural networks are used for option pricing. The first method applies the ANN as a quasi-parametric option-pricing model, by using the inputs of BS model as input neurons and the market price of the option as the target neuron. The second method readily accepts most of the assumptions of the model, with an exception to those of constant volatility and constant risk-free-rate. The latter proposes an augmented forecasting model for the volatility of the underlying asset, detailed in section 2.6.2 and then feeds it to the Black Scholes model (Ahmad & Wilmott, 2005). In the following section we are briefly going to present the literature on both methods analyzing the advantages and drawbacks of each approach.

### 3.2.1 Neural networks as "option pricing" models

Applying the ANN as a quasi Black-Scholes model means using the S/X (Moneyness ratio), r (risk free asset rate), T (time to maturity) and $\sigma_i$ volatility as input neurons to predict the option price. The target neuron of the ANN is either the option market price ($C_t^{mkt}$), or the option market price standardized by the exercise price ($C_t^{mkt} / X_t$), or the difference between the standardized predicted model price and market price of the option $\left(C_t^{model} / X_t - C_t^{mkt} / X_t\right)$. *(Fig. 2.)* This approach aims to loosen the rigidity and strict assumptions of Black Scholes model by applying the ANN directly and using it as estimator of the fair option price.

The first article applying such method fed the variables listed above to the network and trained it on S&P 100 option prices from the year of 1990 (Malliaris et al., 1993). The research have shown lower MSE and better forecasting power similarly to Hutchinson et al's who tested the predicting ability of the ANN on the options of the S&P 500 index by using the standardized option market price ($C_t^{mkt} / X_t$) as target variable (Hutchinson et al., 1994). Laybcygier and Connor have forecasted the volatility of the Australian SPI index and were the first to use the difference of the model price and the market price of the option as target variable ($C_t^{mdl} - C_t^{mkt}$), (Lajbcygier et al., 1997).

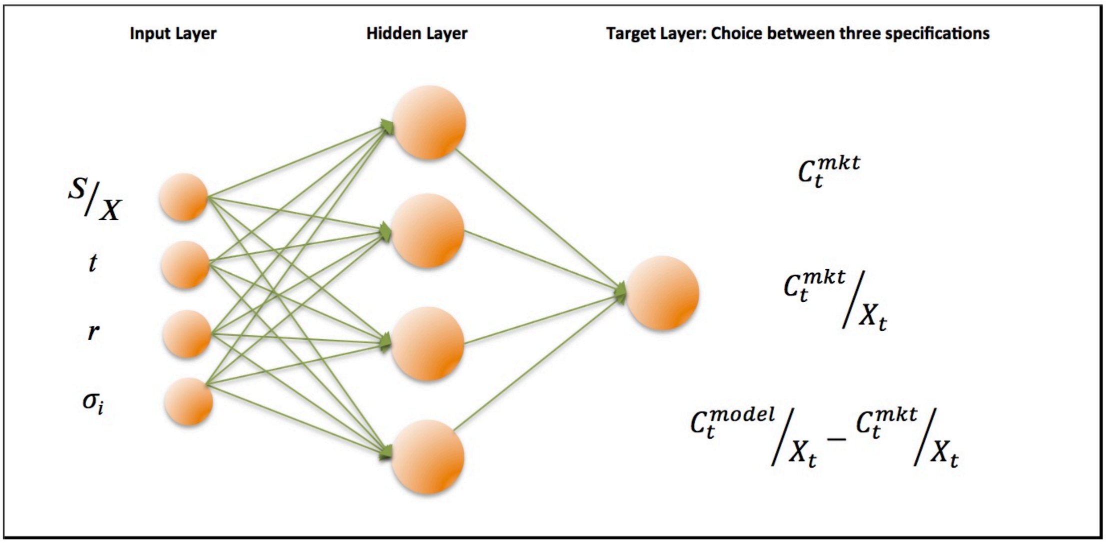


*Fig 2. Artificial Neural Network for option pricing with different target nodes (Source: own editing)*

In the 2000's research on the topic was extended to various markets and assets employing more and more refined hybridized models in order to predict the option prices more accurately. Blynski and Faseruk have tested several variants of the simple ANN with different inputs and compared the results to those of the simple BS model. Both realized and implied volatilities were used as input nodes and although results showed the superiority of the implied volatility measure it remained inconclusive whether ANNs constantly over perform BS method in all economic cycle and environment (Blynski et al., 2007). A hybrid model consisting of two nested neural networks has also been tested for options of individual stocks. The first ANN was used solely for forecasting volatility, while the second model estimated the difference between the model price and actual price of the option (Amornwattana et al., 2007). Asian markets have also been in the scope of the research. Using various non parametric and parametric option pricing models Park et al. have tried to forecast option prices on the Korean Stock Exchange (KOSPI 200) in 20 different time period covering periods of market stress and calm. They concluded that non-parametrical models clearly outperformed Black-Scholes, Heston and Merton models based on the Diebold-Mariano test, which compared the forecasting errors of time series (Park et al., 2014). Saxena applied a hybrid BS-ANN model for the options of S&P CNX NIFTY, one of the most significant index traded on the Indian National Stock Exchange (NSE). The hybrid model produced better results even when multiple error measures were taken into consideration (Saxena, 2008). Others have applied more refined methods to augment the performance of models. The Grey-EGARCH method has been hybridized with an ANN to produce a higher forecasting accuracy on the options of the Taiwan Stock Exchange (TAIEX). Taking into account not only the asymmetry of the volatility, but also the underlying trend in the error terms of the applied time series model the GREY-EGARCH model increased the forecasting efficiency of the model (Tseng et al., 2008).

Despite of the vast literature and use of sophisticated models for forecasting option prices all the abovementioned models have a few flaws. Firstly due to the different time spans, assets and error measures used in the literature it is impossible to rank the models in different articles. Secondly estimating the option price even with the highest accuracy in itself does not lead to abnormal profits, as the articles lack a trading strategy that would capitalize on the augmented forecasting ability and by trading the anomaly realize economic gain. Therefore we suggest that detecting a mispricing in the option prices observed in the market is just a step in the process. The next logical step would be the specification and testing of an automated trading algorithm, which is applicable in diverse economic environment and produces robust results.

### 3.2.2 Parametric OPMs using volatility as inputs derived from neural networks

Very few articles divide the process of option pricing into two separate stages, where neural networks or other machine learning methods would solely be used for estimating the volatility, which in turn would be fed into a parametric option-pricing model determining the fair price of the asset. Blynski and Faseruk suggest the use of a two-step hybrid neural network, where the first network is only used for forecasting the implied volatility, having S/X, T and r as inputs. The second network predicts the difference between the market price and the Black Scholes model price of the option (Blynski et al., 2007). In their neuro-fuzzy system framework Tung and Quek have forecasted the volatility with a neural network, but later on fed it to a fuzzy system leaving parametric models out of the picture completely. (Tung et al., 2011)

## 4. Trading volatility

The trading of volatility as an asset class is not a new phenomenon, as investments banks, option market makers and speculators have been trading volatility for many years. (Skeggs, 2006) Trading volatility means that the investor creates a portfolio, where the exposure to implied and realized volatility is maximized and the exposure to other factors, such as the movements in the price of the underlying is minimized. (Karanasos, 2005) The most popular method of volatility trading is directional volatility trading, where the investor trades the implied volatility versus the historical volatility on the same assets, called vega trading. It can be performed either across different strike prices or different maturities. One can trade directionally either using an option and an underlying or rely entirely on a portfolio consisting options.

### 4.1. Testing the results of volatility forecast by option trading

Generally the explanatory power of the volatility forecast and its goodness-of-fit are tested with different statistical error measures, such as the MAPE, MAE or PE measures. However choosing the appropriate model for predicting volatility is related to the question of how to measure the prediction performance of a model. Given that the 'true' value has no certain measure, comparing the performance of different models is considered to be straightforward when the forecast is applied in several option trading strategies (Sheu & Wei, 2011). As Fischer Black pointed out to test the model performance we give the "economic significance" the preference in contrast to the "statistical significance". In other words ''a model that consistently achieves to identify mispriced options and within a time period produces an amount of trading profits will always be preferred by a practitioner'' (Black and Scholes, 1973). Noh, Engle and Kane tested the validity of the volatility forecasts on the S&P 500 Index with similar measures. In order to test the differences between different methods they tested the volatility forecasting performance using the potential profitability based on some option trading strategies as a metric, evaluated profits from options trading for rival volatility forecasting models and compared them in the same market (Noh& Engle& Kane, 1997). Although the latter article had one flaw compared to the others; Instead of using observed market prices it simulated them, therefore the results of the research had little relevance to actually test the economic profitability in real market environment.

### 4.2. Option trading strategies: delta neutral vs. straddle based strategies

Delta Neutral trading strategy consists of selling and buying options and simultaneously taking opposite positions in the underlying. The delta of a specific stock is defined as the rate of change of the option price with respect to the price of the underlying asset. To offset the impact of the price change to the value of a portfolio consisting options effectively an investor first must calculate the delta for the option. If for example options for shares worth 10,000$ have been bough and the market price of one share is 100$ one can protect from unwanted fluctuation by buying delta amount of underlying share. If the calculated delta in this example is 0,6 than the investor must buy 60 shares to counterbalance the unwanted change in the price of the underlying. The delta neutrality of the portfolio enables us to concentrate on the vega, which is the rate of change of the option price with respect to the volatility of the underlying asset. By creating delta neutral portfolios with high sensitivity to vega one can trade the volatility with a portfolio consisting options and underlying. However the delta hedged portfolio remains insensitive to price change for very little time, given that a small change in time either the delta or the price of the underlying affects the value of the position markedly. Therefore continuous rebalancing of the portfolio is required should one wish to maintain the delta hedged position (Hull, 2015).

One can offset the unwanted price change of the underlying and create vega sensitive combinations from options as well leaving the underlying out of the scope completely. A combination is an option trading strategy in which positions in both calls and puts on the same underlying are taken. The classic combination for gaining exposure to volatility is to buy an at-the money straddle (Carr & Madan, 2002). Straddle is an option strategy with which the investor holds both a call and a put with similar exercise price and maturity. This is a recommended strategy if the investor expects the price of the underlying to move significantly, but is unsure as to which direction it will move. Resulting in an almost delta neutral and highly vega sensitive position the trader benefits from the movement of the volatility (Tung et al., 2011). Should an investor expect the volatility to rise in the foreseeable future he can purchase a straddle by buying both a long call and put option for the same underlying, with the same maturity and exercise price (bottom straddle). On the other hand if he expects the volatility to decrease or he expects a relative calm in the fluctuation in the price of the underlying he can sell a straddle by writing both a call and put with similar maturity and exercise price for the same underlying. The latter, also called top straddle is a riskier strategy than the bottom straddle given that the loss arising from unexpected large movement is unlimited (Hull, 2015). In general ATM call and put options with more than 15 days of maturity were used for straddle trading strategies in past research. Not only do they prove to be fairly priced and more liquid, but also trades at irrational prices due to illiquidity and fear do not usually take place in this segment of the option market (Bartels & Lu, 2000; Guo, 2000; Ahoniemi, 2008).

**4.3 Previous studies on option trading strategies with volatility estimation**

There is a limited amount of scholarly work that applies the framework where the estimation of volatility is closely followed by examining whether options in the market are fairly priced and finally exploits pricing anomalies by establishing a successful trading strategy. Based on the following trading strategy we can divide the studies into two subcategories: Those trading with delta hedging strategy and those applying straddle based strategies. Hutchinson et al. have proposed the estimation of out of sample option prices with ordinary least squares regression and three neural networks. After comparing the resulting model option prices to those observed in the market they initiated a highly successful trading strategy using delta neutral hedging approach. The models were applied to S&P 500 futures options from 1987 to 1991 (Hutchinson et al., 1994). Although this paper estimated the option price with a neural network used as a quasi-Black-Scholes formula it was the first to apply trading strategy with a neural network. Harvey and Whaley readily assumed that true conditional volatility is unobservable, thus comparing volatility predictions of various models is inefficient. Instead one should use the implied volatility as a proxy of the conditional one and use its forecasted value without benchmarking to other parametrical and non-parametrical models. The research was performed on the option prices of the S&P 100 that are all American type, thus deriving the implied volatility from the BS model would have led to biased results given that the BS is used for European type options only. Instead the article used the binomial model to price options and to derive their implied volatility. Furthermore the article has calculated the difference between the option price and the theoretical price and if it was negative (positive) they purchased (sold) an option and sold (bought) a delta unit of underlying. Although the results showed that volatility and option prices were foreseeable, no abnormal profits could have been gained due to the high level of transaction costs. All in all S&P 100 option market seemed to be efficient in terms that no abnormal profits could be realized taking into account transaction costs (Harvey& Whaley, 1992). Guo has applied both the delta neutral hedging and the straddle based strategy in his article. Applying both the GARCH model estimation and the Implied Stochastic Volatility Regression method (ISVR) the article predicted the future volatility for the dollar/german mark options traded on the Philadelphia Stock exchange. Two agents using predictions from the volatility models traded and the resulting profits of the straddle-based strategy were compared to those of the delta neutral hedging strategy. Furthermore the agent using the estimations of the ISVR model reached significantly higher profits even in the presence of filters and transaction cost. (Guo, 2000)

Sheu and Wei have applied a new approach by incorporating investor sentiment to the estimation of future volatility. After having tried several time spans of past volatility estimation, forecasting future volatility for 15 days from the data of the preceding 60 days seemed the best option. Based on the forecasted direction of volatility long or short straddle were constructed from ATM options for the main stock index of Taiwan, the TAIEX. Results have shown that models recruiting sentiment levels proved to be more profitable than those lacking sentiment indicators (Sheu & Wei, 2011). Ahoniemi examined the power of forecasting methods on the VIX index. For estimating volatility the ARIMA(1,1,1), the ARIMA(1,1,1)-GARCH(1,1), the ARIMAX(1,1,1) and the ARIMAX(1,1,1)-GARCH(1,1) models were used and based on their MSE values the model with the best explanatory power was selected (ARIMA-GARCH). Without feeding the observed volatility to any option pricing models the article created either a long or short straddles from ATM calls and puts based on the forecasted direction of VIX index. In order to avoid unwanted excess transaction costs and to leave out the weakest signals filters of 0,1%, 0,2% and 0,5% were applied to the projected directional change of VIX. Options with the nearest maturity, always between 15 and 45 days were selected and the results showed considerable excess profits (Ahoniemi, 2008). Finally it was Tung and Quek who applied more sophisticated volatility-forecasting methods in hands with straddle trading strategy. They divided the process into two parts, by creating the volatility projection (VPM) and trading decision modules (TDM) separating the problem into giving an accurate forecast and creating an optimal trading strategy. The use of evolving fuzzy semantic memory model, which is a type of neuro-fuzzy network with neural type estimation and fuzzy logic based if-than decision rules enabled the authors to incorporate technical analysis to the strategy. In the article both realized and implied volatility of Hang Seng Index (HSI) were calculated, deriving the implied volatility from first in/out the money calls and puts and forecasting with a neural network using the lagged variables of the time series of both volatility measures. After benchmarking the forecasting error measures of the model to those of other data mining techniques the neuro-fuzzy network proved to have the best generalization abilities. They have applied the trading strategy and concluded that the resulting daily profits of the network have highly over performed those of other models (Tung et al, 2011). The inputs, targets, and results of the models are summarized in the table below Besides the data mentioned above, the table contains the type of volatility forecasted by the model, the time-span of the forecast, the results and the implication for market efficiency *(Table 1.)*.

| **Author** | **Model used** | **Input** | **Target** | **Vol. type** | **Volatility time span/forecast** | **Trading strategy** | **Results** | **Market efficiency** |
|---|---|---|---|---|---|---|---|---|
| **Sheu,Wei (2011)** | OLS-AR | historic vol. $\sigma_{60}$ | Future Volatility, $\sigma_{60}$ realized(t+1) | realized, historic | $\sigma_{60}$ forecasted for 5,10,15, 20 days | ATM options with monthly maturity, straddle held till cash settlement | On average 15,84% monthly return | Sentiment indicator has a + impact on trading return |
| **Quek, TUng (2011)** | Neural fuzzy network | AR(9) $\sigma_{30}$ and implied volatility (t-i) | $\sigma_{30}$ and implied volatility (t+1) | historic and implied | 30 days | Based on the MACD rule long/short straddle form ATM options at $_{t}$, liquidation at $_{t+1}$ | Implied volatility outperform historic and model based vol. | Ineff. mrkts, as strategy on HSI options result in abnormal ret |
| **Panayiotis et al (2008)** | ANN | S/X, T, r, CBOE VIX, hist. vol, skewness, curtosis | Ann to estimate option price difference | implied | 30 days | Delta neutral strategy held as long as profitable/ no daily readjustment | Corradu Su parametric model overperforms BS model | Hybrid model produces abnormal returns |
| **Guo (2000)** | Hull-White modell, GARCH, ISVR | GARCH, ISVR method | $\sigma_{30}$ and implied volatility (t+1) | historic and implied | 30 days | Agents trade with both delta neutral and straddle strat from $_{t}$ to $_{t+1}$ Several ATM option pair P/L as averaged (100$) | Significant profit can be achieved with filters on volatility change. | Market is efficient after 1% tr. cost is applied to trades. |
| **Engle, Kane, Noh (1993)** | EGARCH, GARCH | S&P 100 returns | volatility at t+1 | model-based | Options for several maturities upt to 9 months | Artificial model for options with 1 day to 1 year maturity and X at 1$ | Significant abnormals profits are achievable | Market is inefficient as GARCH agent erans abnormal profits |
| **Harwey, Whaley (1992)** | OLS regression | S&P 500 returns | volatility at t+1 | implied | implied for puts and calls separately from BS | Delta neurtal trading strategy | Forecast is accurate, but taking into account tr. cost abnormal returns are nor achievable. | Abnormal returns are not possible, market is efficient |
| **Bartles, Lu (2000)** | EGARCH, GARCH | GARCH, EGARCH family models | volatility at t+1 | implied, historic, model based | implied volatility for 30 days (t+1), historical for 15 days | Long/short straddle from options with closest maturity between 15 and 45 days starting at day t and ending at day t+1 | Positive yield is achiavable from trading strategy with filters | Markets are inefficient, but tr. cost are marked as 0,1% |
| **Ahoniemi (2008)** | ARIMA, ARIMA-GARCH, ARIMAX models | VIX index | volatility at t+1 | implied | implied volatility for 22 days (t+1) | Long/short straddle from options with closest maturity between 15 and 45 days starting at day t and ending at day t+1 | Positive yield is achiavable from trading strategy | No inplication for market efficiency as transaction cost have not been acc. for. |

*Table 1. Summary of studies on option trading strategies with volatility estimation (Source: own editing)*

## 5. A multicomponent model to forecast volatility and trade options

As detailed in the previous section of this article several papers have tried to apply enhanced volatility forecasting to option trading strategies producing inconclusive results. The difficulty of conducting research on the field lies in the fact that both the methodology and the trading strategy applied are not thoroughly documented in the papers, thus forcing one to make inferences while building an appropriate model.

This thesis aims to create and test a complex, multicomponent model for the purposes of volatility forecasting and option trading in various economic environments *(Fig. 3.)*. Following the date preprocessing and the estimation of implied volatility from observed option market prices the model first specify and fit an appropriate ARMA and GARCH family model to forecast the conditional volatility of the underlying's returns. Secondly we calculate the realized volatility of the underlying return with a rolling method for several time spans (21, 42 and 64 working days) and also derive the implied volatility measures from the corresponding option prices. Furthermore we feed the abovementioned implied volatilities and conditional volatility alongside with the lagged variable of the realized volatility and other external explanatory variables to the neural network. We then train and validate the network using the variables listed above as input nodes and the implied volatility at day $t$ as target node.

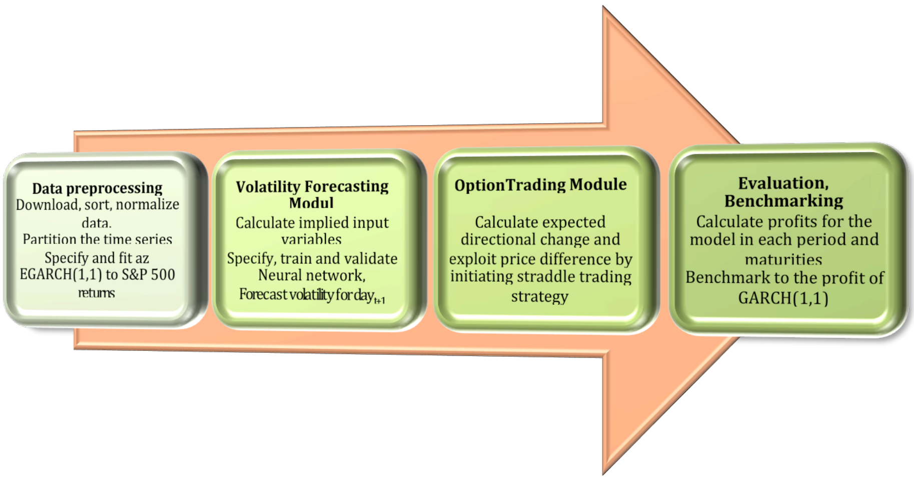


*Fig 3. The structure of the multicomponent model (Source: own editing)*

Getting a highly reliable estimation for the future volatility is not the goal of this article but merely a tool, on which we need to further capitalize, by feeding it to the second module of the model. The Option Trading Module engages in trading based on two criteria. First it calculates the level of change in the predicted volatility and using a filter decides whether the expected change in the level of volatility would generate enough profit to offset the incurring transaction costs, or in other words whether the model should engage in trading at all. Furthermore by substituting the forecasted implied volatility to the Black Scholes option pricing formula we get the hypothetical prices for both call and put options. The algorithm than compare the price of the straddle created from hypothetical calls and puts to the one created from observed market prices and engages in option trading with straddles accordingly. The model trades on daily bases throughout the business week and proceeds from previous transactions are continuously invested during the period. For benchmarking purposes the forecast of GARCH model were used by an additional agent, whose trade decisions are based only on the direction of forecasted conditional volatility.

Finally the portfolio values for both agents are calculated for the whole period hypothesizing a 100 $ worth initial investment. Alongside returns Sharpe ratios are also presented for both agents to facilitate benchmarking purposes. The efficiency of the volatility forecast of the neural network is measured by both the hit rate and the MSE of the forecast in each period. In addition to test the change of predictability with respect to increase in maturity forecasting errors for different tenors are compared with the Diebold-Mariano test. As the research is conducted on different time periods and maturities it offers an insight to a large extent of the option market's efficiency, which in turn can be tested by comparing the profitability of trading in different time periods. Lastly the sensitivity of the portfolio values to transaction costs and to the level of filter is also presented so that further inferences could be draw on the effect of external parameters to the profitability of the trading strategy.

# 6. Data preprocessing and input variables

## 6.1 Data and Time span

The research was conducted on a multidimensional dataset consisting both the time series of the S&P 500 index and data on its options from 2007.01.01- to 2015.09.15. The dataset included not only the closing price for the index, but the corresponding volume as well. The option data itself contained more than 1000 data points for a day, including the last, ask and bid prices, implied volatilities, volume for both call and put options for a wide range of exercise price.

The data was downloaded from the Bloomberg[1]. The data consisted of the daily closing prices and the volume of contracts in dollars for the underlying index, the closing prices of NASDAQ and VIX index and daily volumes for both call and put options for the S&P 500. Bloomberg provides data on historic option prices in the form of option chains, which is an artificially created time series reflecting the price change of an option in time with fixed exercise price and maturity. For analytical purposes the data had to be rearranged, so that at any given day the actual option mid, bid and ask closing price for a wide range of exercise prices and 3 maturities are shown. *(Fig. 4.)* Therefore by creating a Bloomberg-like screen for every day of the period one can formulate a trading strategy based on actual transaction data with volumes reflecting the market environment at that time. Originally the data consisted of more than 12,320,000 observations for mid, bid, ask prices and volumes for different maturities and exercise prices and for both call and put options.

Due to the extreme high dimensionality of the data the research had to be restricted to the analysis of near ATM options, thus leaving the examination of dynamics of the OTM and ITM options for further studies. We have further limited the model to trade at the mid prices of both call and put options, but accounted for appropriate transaction cost incorporating the bid-ask gap. The resulting 30.800 near ATM mid call and put price were taken in the model as the true representation of the market. Choosing At-The-Money or near At-The-Money options, with Moneyness (S/X) between 0,98 and 1,03 is an economically viable step as a significant proportion of total trades takes place within this price range and large amount of liquidity is provided to establish a trading strategy. Previous research has also provided support for using near ATM options for trading.

[1] I'm expecially grateful to the Corvinus University of Budapest and all the supporters of the Financial Laboratory at the University for subscribing to the services of Bloomberg. Without the availability of the extensive amount of data downloaded via this terminal this article couldn't have been written.

| Ticker | SPX | Type | Index | | SPX | Index | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Dátum | 9/26/14 | Maturity | 10/18/2014 | S&P 500 | 1982,85 | Call/Put | C | P | 10/18/14 | | Day to maturit | 22 | |
| Moneyness | Excercise price | Ticker | PX LAST | IVOL MID | PX VOLUME | PX BID | PX ASK | Ticker | PX LAST | IVOL MID | PX VOLUME | PX BID | PX ASK |
| 0,782 | 1550 | SPX 10/18/2014 C1550 Index | 458,2 | 45,055 | 2 | 431,3 | 433,3 | SPX 10/18/2014 P1550 Index | 0,4 | 40,162 | 216 | 0,25 | 0,3 |
| 0,807 | 1600 | SPX 10/18/2014 C1600 Index | 415,5 | 40,532 | 2 | 381,4 | 383,2 | SPX 10/18/2014 P1600 Index | 0,4 | 37,022 | 4959 | 0,4 | 0,45 |
| 0,832 | 1650 | SPX 10/18/2014 C1650 Index | 348,8 | 36,478 | 10 | 331,5 | 333,4 | SPX 10/18/2014 P1650 Index | 0,55 | 33,563 | 203 | 0,5 | 0,6 |
| 0,857 | 1700 | SPX 10/18/2014 C1700 Index | 272,9 | 32,347 | 1 | 281,9 | 283,6 | SPX 10/18/2014 P1700 Index | 0,8 | 29,359 | 3607 | 0,65 | 0,85 |
| 0,883 | 1750 | SPX 10/18/2014 C1750 Index | 239,18 | 28,514 | 2 | 232,3 | 234 | SPX 10/18/2014 P1750 Index | 1,2 | 27,071 | 3585 | 1 | 1,4 |
| 0,908 | 1800 | SPX 10/18/2014 C1800 Index | 183,3 | 24,542 | 9 | 183 | 185 | SPX 10/18/2014 P1800 Index | 1,8 | 23,795 | 1159 | 1,7 | 2,1 |
| 0,933 | 1850 | SPX 10/18/2014 C1850 Index | 122 | 20,955 | 1732 | 134,5 | 136,3 | SPX 10/18/2014 P1850 Index | 3,2 | 20,372 | 1674 | 3 | 3,7 |
| 0,958 | 1900 | SPX 10/18/2014 C1900 Index | 87,65 | 17,834 | 54 | 87,7 | 89 | SPX 10/18/2014 P1900 Index | 6,35 | 17,369 | 7308 | 6,1 | 6,8 |
| 0,983 | 1950 | SPX 10/18/2014 C1950 Index | 45,5 | 14,423 | 269 | 45,3 | 46,1 | SPX 10/18/2014 P1950 Index | 14 | 14,082 | 13011 | 13,3 | 13,9 |
| 1,009 | 2000 | SPX 10/18/2014 C2000 Index | 12,5 | 10,79 | 7891 | 12,5 | 13,1 | SPX 10/18/2014 P2000 Index | 29,48 | 10,588 | 341 | 30,2 | 31,2 |
| 1,034 | 2050 | SPX 10/18/2014 C2050 Index | 0,7 | 8,213 | 5246 | 0,75 | 0,9 | SPX 10/18/2014 P2050 Index | 83 | 7,529 | 61 | 67,9 | 69,7 |
| 1,059 | 2100 | SPX 10/18/2014 C2100 Index | 0,15 | 10,084 | 564 | 0,1 | 0,15 | SPX 10/18/2014 P2100 Index | 110 | 8,1 | 10 | 117,1 | 118,9 |
| 1,110 | 2200 | SPX 10/18/2014 C2200 Index | 0,05 | 16,532 | 21 | 0,05 | 0,1 | SPX 10/18/2014 P2200 Index | 191 | 21,117 | 3000 | 217 | 218,8 |
| | | Maturity | 11/22/2014 | | | | | | 11/22/14 | | Day to maturit | 57 | |
| Moneyness | Excercise price | Ticker | PX LAST | IVOL MID | PX VOLUME | PX BID | PX ASK | Ticker | PX LAST | IVOL MID | PX VOLUME | PX BID | PX ASK |
| 0,756 | 1500 | SPX 11/22/2014 C1500 Index | 477 | 33,986 | 1 | 478,2 | 480 | SPX 11/22/2014 P1500 Index | 1,1 | 32,229 | 226 | 1,05 | 1,1 |
| 0,782 | 1550 | SPX 11/22/2014 C1550 Index | 428 | 30,399 | 1 | 428,6 | 430,5 | SPX 11/22/2014 P1550 Index | 1,45 | 30,283 | 213 | 1,45 | 1,55 |
| 0,807 | 1600 | SPX 11/22/2014 C1600 Index | 382,35 | 28,265 | 1 | 379,1 | 381 | SPX 11/22/2014 P1600 Index | 1,9 | 28,104 | 2280 | 1,9 | 2,1 |
| 0,832 | 1650 | SPX 11/22/2014 C1650 Index | 363,2 | 26,613 | 8 | 329,9 | 331,7 | SPX 11/22/2014 P1650 Index | 2,88 | 26,363 | 840 | 2,7 | 2,85 |
| 0,857 | 1700 | SPX 11/22/2014 C1700 Index | 272,4 | 24,386 | 7 | 281 | 282,8 | SPX 11/22/2014 P1700 Index | 3,8 | 23,7 | 108 | 3,5 | 3,8 |
| 0,883 | 1750 | SPX 11/22/2014 C1750 Index | 259,14 | 22,264 | 1 | 232,7 | 234,5 | SPX 11/22/2014 P1750 Index | 5,15 | 22,156 | 2430 | 5,3 | 5,8 |
| 0,908 | 1800 | SPX 11/22/2014 C1800 Index | 192,9 | 20,202 | 1 | 185,5 | 187,1 | SPX 11/22/2014 P1800 Index | 8 | 19,994 | 4301 | 7,7 | 9 |
| 0,933 | 1850 | SPX 11/22/2014 C1850 Index | 163,47 | 18,137 | 49 | 139,7 | 141,2 | SPX 11/22/2014 P1850 Index | 12,15 | 17,964 | 2492 | 11,8 | 12,7 |
| 0,958 | 1900 | SPX 11/22/2014 C1900 Index | 95,7 | 16,066 | 1 | 96,6 | 97,8 | SPX 11/22/2014 P1900 Index | 19 | 15,899 | 1595 | 18,4 | 19,3 |
| 0,983 | 1950 | SPX 11/22/2014 C1950 Index | 56 | 13,904 | 132 | 57,6 | 58,6 | SPX 11/22/2014 P1950 Index | 29,8 | 13,766 | 6891 | 29,2 | 30,3 |
| 1,009 | 2000 | SPX 11/22/2014 C2000 Index | 26,05 | 11,675 | 3214 | 25,8 | 26,6 | SPX 11/22/2014 P2000 Index | 48,1 | 11,716 | 69 | 47,3 | 48,4 |
| 1,034 | 2050 | SPX 11/22/2014 C2050 Index | 7 | 9,478 | 1998 | 6,8 | 7 | SPX 11/22/2014 P2050 Index | 90,65 | 9,5 | 5 | 77,8 | 79,6 |
| 1,084 | 2150 | SPX 11/22/2014 C2150 Index | 0,22 | 9,699 | 2 | 0,05 | 0,7 | SPX 11/22/2014 P2150 Index | 153,6 | 7,74 | 1 | 170,9 | 172,8 |
| | | Maturity | 12/20/2014 | | | | | | 12/20/14 | | Day to maturit | 85 | |
| Moneyness | Excercise price | Ticker | PX LAST | IVOL MID | PX VOLUME | PX BID | PX ASK | Ticker | PX LAST | IVOL MID | PX VOLUME | PX BID | PX ASK |
| 0,706 | 1400 | SPX 12/20/2014 C1400 Index | 596,7 | 33,998 | 2 | 575,9 | 577,8 | SPX 12/20/2014 P1400 Index | 1,5 | 32,041 | 6 | 1,2 | 1,3 |
| 0,731 | 1450 | SPX 12/20/2014 C1450 Index | 550,15 | 31,133 | 2 | 526,3 | 528,2 | SPX 12/20/2014 P1450 Index | 1,7 | 30,423 | 255 | 1,55 | 1,75 |
| 0,756 | 1500 | SPX 12/20/2014 C1500 Index | 502,1 | 30,201 | 2 | 476,8 | 478,8 | SPX 12/20/2014 P1500 Index | 2,2 | 28,827 | 190 | 2,05 | 2,25 |
| 0,782 | 1550 | SPX 12/20/2014 C1550 Index | 455,3 | 28,107 | 18 | 427,7 | 429,7 | SPX 12/20/2014 P1550 Index | 3 | 27,313 | 45 | 2,85 | 3,2 |
| 0,807 | 1600 | SPX 12/20/2014 C1600 Index | 392,12 | 26,302 | 1 | 378,8 | 380,7 | SPX 12/20/2014 P1600 Index | 4,87 | 25,846 | 18 | 3,8 | 4,3 |
| 0,832 | 1650 | SPX 12/20/2014 C1650 Index | 338 | 24,453 | 500 | 330,2 | 332,1 | SPX 12/20/2014 P1650 Index | 5 | 24,12 | 17 | 5,1 | 5,7 |
| 0,857 | 1700 | SPX 12/20/2014 C1700 Index | 274,17 | 22,735 | 3 | 282,1 | 284,1 | SPX 12/20/2014 P1700 Index | 7 | 22,459 | 265 | 7 | 7,7 |
| 0,883 | 1750 | SPX 12/20/2014 C1750 Index | 222,8 | 21,024 | 3 | 234,9 | 236,8 | SPX 12/20/2014 P1750 Index | 9 | 20,825 | 1012 | 9,6 | 10,5 |
| 0,908 | 1800 | SPX 12/20/2014 C1800 Index | 188 | 19,342 | 20 | 189 | 190,8 | SPX 12/20/2014 P1800 Index | 14 | 19,197 | 121 | 13,5 | 14,5 |
| 0,933 | 1850 | SPX 12/20/2014 C1850 Index | 166 | 17,633 | 31 | 145 | 146,6 | SPX 12/20/2014 P1850 Index | 19,65 | 17,508 | 664 | 19,3 | 20,4 |
| 0,958 | 1900 | SPX 12/20/2014 C1900 Index | 94 | 15,884 | 122 | 103,3 | 104,9 | SPX 12/20/2014 P1900 Index | 28 | 15,742 | 1559 | 27,6 | 28,8 |
| 0,983 | 1950 | SPX 12/20/2014 C1950 Index | 66,5 | 14,088 | 125 | 66,1 | 67,2 | SPX 12/20/2014 P1950 Index | 39,9 | 13,938 | 147 | 40 | 41,3 |
| 1,009 | 2000 | SPX 12/20/2014 C2000 Index | 35,3 | 12,287 | 3224 | 34,9 | 36 | SPX 12/20/2014 P2000 Index | 57,5 | 12,11 | 2172 | 58,8 | 60,1 |
| 1,034 | 2050 | SPX 12/20/2014 C2050 Index | 13,8 | 10,645 | 265 | 13,7 | 14,5 | SPX 12/20/2014 P2050 Index | 99 | 10,482 | 17 | 87,2 | 88,8 |
| 1,059 | 2100 | SPX 12/20/2014 C2100 Index | 3,85 | 9,676 | 221 | 3,8 | 4,1 | SPX 12/20/2014 P2100 Index | 104,15 | 9,258 | 10 | 126,8 | 128,7 |
| 1,110 | 2200 | SPX 12/20/2014 C2200 Index | 0,48 | 10,229 | 5 | 0,25 | 0,75 | SPX 12/20/2014 P2200 Index | 208,5 | 11,145 | 2 | 223,1 | 225 |
| 1,135 | 2250 | SPX 12/20/2014 C2250 Index | 0,2 | 10,758 | 500 | 0,1 | 0,3 | SPX 12/20/2014 P2250 Index | 266,7 | 12,546 | 500 | 273 | 274,8 |

*Fig 4. Input data for the multicomponent model (Source: own editing, Bloomberg)*

Not only do at-the-money S&P 500 options have the highest trading volume (Buraschi & Jackwerth, 2001), but also market participants wish to make a bet on future volatility are more likely to trade options with this moneyness, than with those with in-the-money or out-of-the-money (Ni et al., 2008). In addition Bollen and Whaley (2004) have observed that the highest sensitivity to volatility is observed at the class of near ATM options. Therefore it was a logical step to choose near ATM options for the trading simulations. To create a consistent trading strategy throughout the whole period options were classified into three classes (short, medium and long) based on their time to maturity *(Table 2.)*.

| Upper and lower boundaries of maturity classes in days | | |
|---|---|---|
| Maturity class/ Modell | Lower boundary | Upper boundary |
| **1st maturity class** | *15* | *45* |
| **2nd maturity class** | *46* | *75* |
| **3rd maturity class** | *76* | *105* |

*Table 2. Upper and lower boundaries of maturity classes in days (Source: own editing)*

For instance in January 2011 a near ATM option expiring in April 2011 was classified and traded in the "long maturity" category until mid February, when its time to maturity expressed in days reached to 75 days and was reclassified to the "medium maturity" category. In the beginning of April 2011 as the time to maturity of this option expressed in days fell below 15 days the model ceased to trade with it. Naturally as the price of the underlying, thus the near ATM exercise price changed constantly. The option traded on a given day was a completely different from that one traded the day before.

The resulting database consisted of three tables of three maturity classes for every day that contained the traded call and put options for a wide range of exercise prices. Just as if we were at the given day watching the Bloomberg screen the panel showed the last price, the estimated implied volatility, the volume and the ask and bid price of a given option for a given maturity and exercise price. Unfortunately implied volatility estimations were only available from 2014, therefore we needed to estimate them for earlier periods.

The time series were partitioned in order to test the validity and efficiency of the model in different economic environments: both in periods of market stress and calm. The time series spanning through almost a decade from 2006.12.26 to 2015.09.02 was divided into 3 periods. The first, from 2006.12.26 to 2009.12.31 was characterized by strengthening volatility and by huge jumps in option prices toward the end of 2008 *(Period 1.)*. Although the second period from 2010.12.30 to 2013.12.30 covered the European debt crisis and the United States debt ceiling crisis it showed considerably calmer market environment than the previous period *(Period 2.)*. The last period, slightly overlapping the previous in the learning sample provides forecasts for 2014 and 2015 reflecting the least turbulent market environment with low level of implied volatilities and steadily increasing asset prices *(Period 3.)*.

### 6.2 Estimating conditional volatility

As pointed out earlier in section 2.5 conditional volatility models readily capture the otherwise overlooked stylized facts in financial time series such as volatility clustering and thus they provide a better tool for modeling and forecasting volatility. Based on previous research on the topic we have specified and fitted an EGARCH(1,1) model to the time series of the underlying S&P 500 returns *(Fig 5)*. By capturing not only the autoregressive effects but also the asymmetry in volatility this method offers more accurate forecasting method compared to the GARCH(1,1) model. The model was specified and fitted with a rolling window method.

The parameters of the models were not estimated for the whole time series, but by taking only the data for the previous 21 days into consideration. This way the estimation reflected the impact of recent events to the structure of the volatility, reacted more dynamically for sudden jumps and in turn provided more accurate forecasts. We have compared the Akaike and Bayes-Schwartz information criteria of the model to that of the GARCH(1,1) and found that EGARCH fits better and lacks the sign bias apparent in the former model. As the estimation readily reflects the changes in the volatility of S&P 500 returns it is fed into the Artificial Neural network along with explanatory other variables, hoping that the additional information on conditional volatility will result in an efficient and accurate forecast.

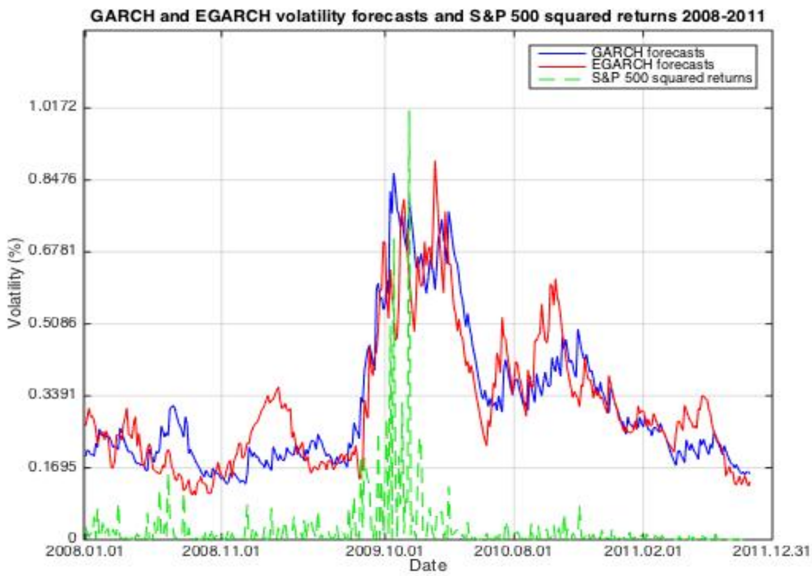


*Figure 5. Fitted GARCH& EGARCH models and the S&P 500 squared returns*

*(Source: own editing)*

The GARCH forecast was further utilized for benchmarking purposes. An additional agent using the GARCH forecasted volatility as an input was also set up, whose trade decisions were solely based on the directional change in the conditional volatility. Although the implied volatility and the model based conditional volatility largely differ, the GARCH(1,1) model is extensively used in the literature for benchmarking purposes (Bartels & Lu, 2000; Guo, 2000; Ahoniemi, 2008).

# 7. Volatility forecasting and Option trading

## 7.1 Volatility Forecasting Module

The Volatility Forecasting Module relies on the returns of the underlying index, the forecasted volatility of EGARCH(1,1) model and the database of near-ATM call and put option closing prices as input data. The module first calculates or derives implied data and creates inputs nodes for the Neural Network by standardizing and transforming the data. Previous research has shown that neural networks do perform better on transformed dataset and in turn produce more accurate forecast (Atsalakis, 2009). After feeding the derived and other external nodes to the network it trains on the data of 250 business days and by applying the specified network it forecasts for the next 30 business days. We apply the rolling window method proposed by Hutchinson et al and the forecasts for the following 30 days are based on a new network specified, trained and validated on data from the previous 250 working days. Finally the forecasted volatility is fed to the Option Trading module.

Selecting the set of optimal explanatory variables for a neural network is not a straightforward task to handle. Based on Tung et al. (2011) we have used the first, second and third lagged value of the time series of the implied volatility. The forecasted conditional volatility of the EGARCH model was also a key input. The latter has a superior explanatory power based on its high relative contribution factor detailed in the literature (Donaldson & Kamstra, 1997; Roh, 2007; Tseng et al., 2008; Hajizedah et al., 2012). We are following Hajizedah et al. (2012), who have used both the daily closing price and traded volume of the S&P 500 in hands with the closing price of the NASDAQ index to produce a reliable estimate for the volatility of the S&P 500. Also both the total traded volume of call and put options were used as input nodes to model the scale of trading on the option market (Guo, 2001). Although the VIX index accurately models the implied volatility of the S&P 500 for 30 days it could not have been used as target in the model as it takes only into account the volatility of a specific range of options and calculates a composite measure of implied volatility. As we have aimed to give a forecast for the implied volatility of call and put separately and for longer maturities we have discarded the VIX and calculated the implied volatility from observed prices. However for measuring the accuracy of the forecast we have applied a method used by other researchers and calculated a mean implied volatility. This mean was derived from both the near at the money call and put options and then averaged in every maturity class using the equation below, where $t$ denotes the day and $i$ the different maturity classes (Tung et al. 2011).

$$IV_{average\_t} = \frac{\left(IV\_Call_{i,t} + IV\_Put_{i,t}\right)}{2}$$

The implied volatility for a given option was calculated using the reversion of the Black-Scholes equation and Newton-Raphson iteration. Given the known parameters (S, K, r, T and c or p) the method substitute a sigma value to the equation below and finds the root of the equation by comparing the observed market price and BS price of the options and changing the volatility iteratively. The volatility is calculated as follows:

$$\sigma_{n+1} = \sigma_n - \frac{V_{mkt} - V_{BS}(\sigma_n)}{\frac{\Delta V_{BS}(\sigma_n)}{\Delta\sigma}}$$

, where the $\sigma_n$is the implied volatility, $V_{mkt}$ is the observed option price on the market, $V_{BS}(\sigma_n)$ is the calculated BS price given the sigma and $\Delta\sigma$ is the change in the level of volatility (Christou, 2010). Having created the time series of implied volatilities for all the maturity classes and for both calls and puts we have obtained six time series for the implied volatilities and have used the first, second and the third lag of each variable as input nodes. The 10 variables used for forecasting the implied volatility at time (t) as target variable were as follows:

| | | |
|---|---|---|
| 1. | 1st lag of realized volatility | $RV_{t-1}$ |
| 2. | 1st lag of implied volatility | $IV_{t-1}$ |
| 3. | 2nd lag of implied volatility | $IV_{t-2}$ |
| 4. | 3rd lag of implied volatility | $IV_{t-3}$ |
| 5. | Forecasted conditional volatility EGARCH(1,1) model | $Cond.vol_{t-1}$ |
| 6. | S&P 500 Index Call Option total traded volume (unit) | $VOL\_C_{t-1}$ |
| 7. | S&P 500 Index Put Option total traded volume (unit) | $VOL\_P_{t-1}$ |
| 8. | SPX traded volume in USD | $Volume_{t-1}$ |
| 9. | S&P 500 Index Price | $SPX_{t-1}$ |
| 10. | NASDAQ Index Price | $NSDQ_{t-1}$ |

We have used the Neural Network Toolbox$^{TM}$ of Matlab for specifying and fitting a neural network. All input data have been rescaled to fall between -1 and 1 by the "mapminmax" function of the software. The time series of the input data for a given time period was partitioned as follows. The network was taught on the first 200 observations and validated the results on the following 50. Than the specified network produced forecast for following 30 days. Next the rolling window for learning-validation-testing sample rolled over 30 days and specified and taught the network based on the information set of the next 250 observations *(Fig. 6.)*.

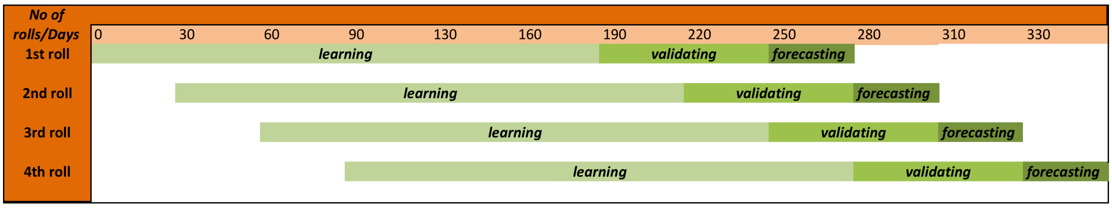


*Figure 6. Rolling learning-validating-testing window (Source: own editing)*

Allocating relatively large amount of data (250 observation) for learning and validating purposes enables the network to incorporate all types of market behavior and extremities and thus produce better forecast. As for the test, or forecast sample we believe that 30 days is long enough to avoid unnecessary re-specification of the network and short enough to avoid disregarding underlying structural changes in market environment.

As the number of neurons in the hidden layers are subject to specification, and has a huge impact on the goodness-of-fit of the model we have run the model to specify and fit networks with different number of neurons (16 to 20) in the hidden layers. The Levenberg- Marquard algorithm was applied to solve the optimization problem and relying on gradient descent the algorithm iterated to find the best fitting parameters of the network euphemized as learning process. We have run the described process 100 times on a given layer, than averaged the forecast and calculated the MSE of the goodness of fit based on the equation below:

$$\mathrm{MSE\_ANN}_{\phi} = \frac{1}{T}\sum_{t=1}^{T}(\mathrm{IV_t} - \mathrm{FV}_t)^2$$

, where $\phi$ stands for number of neurons in the hidden layer, T for the length of the time series and $\mathrm{RV_t}$ and $\mathrm{FV}_t$ for the actual implied and forecasted volatility respectively. Based on the MSE of the validation set the Volatility Forecasting Module selected the optimal number of neurons in the hidden layers and produced forecasts with the corresponding specified network for the following 30 days. After having stored the resulting volatility estimations the network rolled over to the next period in the time series subsample. Finally the time series of volatility estimates for all rolling sample were summarized and fed to the Option Trading Module. The process is shown on the figure below *(Figure 7.)*.

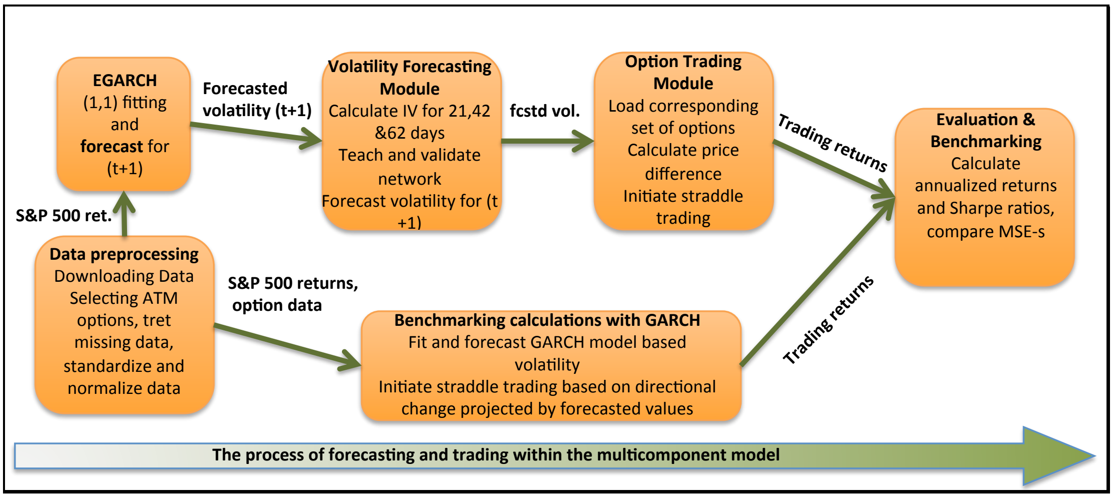


*Figure 7. Mechanism of the model (source: own editing)*

We have applied two methods to test the goodness of fit of the volatility forecast. As the neural network heavily relies on the MSE of the forecasted value it served as a primary tool for measuring accuracy. The directional accuracy of the forecast plays an even larger role when forecasts are further utilized in trading strategies if such strategies base their decisions on the predicted direction of the variable. In volatility forecasting the directional accuracy is reflected in the hit rate and can be expressed as the ratio of correctly guessed direction of movements in volatility. If this value is below 50% the forecast shows no directional accuracy, if its between 50% and 55% we assume that the accuracy is weak and when the ratio of correctly guessed movements reaches over 55% we can talk about a reasonable model.

As we aim to compare the forecasting accuracy of models in different maturity classes we first simply compare the MSE values. However should these error measures fall close to each other we need to apply econometrical test to test whether they are statistically different from each other, or in other words whether the forecasting accuracy differs in different maturity classes. The Diebold-Mariano (DM) test is widely used in the literature for comparing predictive accuracy of volatility forecasts (Ahoniemi, 2008; Park et al., 2014). The DM test is a model free test of forecasting accuracy applicable to non-quadratic loss functions and multi period forecasts. The test hypothesize that the distribution of errors are non-Gaussian, with a non zero mean and exhibit serial correlation (Diebold & Mariano, 1995). In case of two forecasts $i$ we define the forecasting error as $e_{it} = \hat{y}_{it} - y_t$ , $i=1,2$ and the loss differential between two forecasts as $d_t = g(e_{1t}) - g(e_{2t})$. Two forecasts have equal accuracy if and only of the loss differential $(d_t)$ has zero expectation for all *t*. The null hypothesis of the test is that the two forecasts have the same accuracy, while the alternative hypothesis states that their level of accuracy differs in such extent that the loss differential is not zero. The test statistics is computed as follows, where *VAR(d)* is an estimate of the unconditional variance of *d*.

$$DM = \frac{\bar{d}}{\sqrt{\frac{Var(d)}{T}}} \qquad H_0: E(d_t) = 0 \;\; \forall t, \text{ and } \; H_1: E(d_t) \neq 0.$$

This statistics is asymptoticaly normally distributed and the null hypothesis is rejected if the computed DM statistic falls outside the range of $\frac{-z_\alpha}{2}$ to $\frac{z_\alpha}{2}$, where $\frac{z_\alpha}{2}$ is the upper z-value from the standard normal table corresponding to half of the desired α confidence level of the test. In MATLAB applying the '*dmtest*' function, developed by Ibisevic (2011) is relatively straightforward as the function gives the DM test statistics as output. In practice when the errors of two volatility forecasts are compared and the value of test statistics fall outside the range $\pm 1{,}96$ we reject the null hypothesis, thus the forecasts are statistically different at 95% confidence level. If however the value fall within the specified range there is no statistical difference between the goodness of fit of the two series.

### 7.2 Option Trading Module

The module is responsible for trading with straddles of call and put options from a predefined dataset and bases its decisions on the difference of calculated hypothetical prices and observed prices of the option the directional change of the volatility forecasted by the Volatility Forecasting Module.

The main inputs of the module are the set of observed market prices for near ATM call and put options, the forecasted volatility from the Volatility Forecasting Module and the time series of forecasts of the GARCH(1,1) model for benchmarking purposes. The module first collects a near ATM call and put option pair closing prices for $day_t$ and $day_{t+1}$, with the former serving as an opening price and the latter as a closing price for the transaction. The option positions are opened with the close quotes on $day_t$ and closed with the close quotes on $day_{t-1}$, which is the day for which the volatility forecast is made. The straddle prices are calculated by summing the corresponding option prices for a given day. The profit for short and long straddle are calculated as follows:

$$\Pi_{t+1}^{long} = \frac{((C_t + P_t) - (C_{t+1} + P_{t+1})) - \gamma}{(C_t + P_t)}$$

$$\Pi_{t+1}^{short} = \frac{(-(C_t + P_t) + (C_{t+1} + P_{t+1})) - \gamma}{(C_t + P_t)}$$

$$\gamma = ((C_t + P_t) + (C_{t+1} + P_{t+1})) * \mathrm{Tr}_{\mathrm{cost}}$$

, where $C_t$, $P_t$, $C_{t-1}$, $P_{t-1}$ are the closing prices for call and put options for $\text{day}_t$ and $\text{day}_{t-1}$ respectively, $\gamma$ denotes the transaction cost in \$ and $\mathrm{Tr}_{\mathrm{cost}}$ is the transaction cost in percent. In this paper we set the level of transaction cost at 1% following the guidance of Guo (2001). Naturally the model would not absorb all the transaction related cost of the bid ask spread, but might serve as an indicator of profitability between different time periods and maturities.

As detailed above in each maturity classes options with the nearest expiration date were used, until the defined number of days before the expiration date of the option, when trading was rolled over to the next expiration date at the given maturity class. Therefore the model starts to trade with an option when its time to maturity reaches the maximum number of days in the 3rd maturity class, continues trading with it through the different maturity classes and cease the trading as it's time to maturity falls below 15 days. Options with maturities below 15 days are out of scope as their IV behaves erratically, due to lack of liquidity, forced selling obligations and other portfolio management issues (Poon and Pope, 2000).

The trading strategy bases its decisions both on the difference between the calculated model price and the observed market price of the straddle adjusted with transaction costs and the filters derived from the change in the level of volatility.

Before the actual trading one needs to create the filter, which is basically a decision rule weather the module should trade on a given day or not. In straddle trading the volatility has to change significantly so that the potential gains offset the incurring transaction costs. Having computed the difference of volatility forecasts for each day we define an appropriate level of change, or in other words a filter below which level of change the model should not engage in trading. Based on the sensitivity analysis we set this value at 1%, which means that the volatility must deviate from its previous value with at least 1% so that unnecessary transaction cost wont absorb the profits.

Furthermore the model substitutes the forecasted call and put implied volatilities into the Black Scholes formula and obtains hypothetical model prices for call and put options ($C_t^M + P_t^M$). Based on previous research we compare the model prices to the observed prices ($C_t^A + P_t^A$) (Ahoniemi, 2008; Guo, 2000). We further develop this comparison by taking into account transaction costs ($\gamma$) defined earlier. The decision rule of the model is as follows. Should the straddle from model prices worth more than that from the observed market prices and the transaction cost the straddle is underpriced, so we engage in a long straddle strategy believing that level of volatility is expected to rise.

$$(C_t^M + P_t^M) \; > \; (C_t^A + P_t^A) + \gamma$$

On the other hand should the straddle from observed market prices worth more than that from the model prices and the transaction cost the straddle is overpriced, so we engage in a short straddle strategy expecting the volatility to fall.

$$(C_t^A + P_t^A) > \; (C_t^M + P_t^M) + \gamma$$

All positions were opened on $\text{day}_t$ were closed on the following day ($\text{day}_{t+1}$) to avoid loss due to delta change in the portfolio. Straddles are only near delta and gamma neutral for a very limited time, and given that intra-day data could not have been obtained we were unable to offset this impact by engaging in a delta neutral strategy. Besides calculating the profits based on the method described above the module also traded with the forecasts from the GARCH(1,1) model parallel in order to evaluate the efficiency of the ANN with a benchmark strategy. Given the unlimited amount of possible loss and the limited gain inherent in the framework of straddle trading the module traded on the first four business days of the week. Positions opened on the last business day of the week were held during the weekend and the potential large-scale move in the price of the underlying coupled with the impact of news on non working days would have resulted in unforeseeable changes in option prices and deteriorated the profitability of the strategy.

The results of the trade were evaluated with the annualized profit and Sharpe ratio for both the agent trading with neural network and the one with the GARCH model and are presented in section 8. Both agents have started trading with a portfolio of 100 $ worth in the beginning of the period and profits were continuously reinvested.

The Sharpe ratio was calculated as follows, where the $\sigma_p$ is the variance $\bar{r}_p$ is the return of the portfolio and $r_f$ is the risk free rate.

$$S_{period} = \frac{\bar{r}_p - r_f}{\sigma_p}$$

Given that we aimed to compare the forecasting ability and the profitability of different tenors, accuracy measures of the volatility forecast are also listed alongside the numbers on profitability. Not only have we presented the corresponding MSE value and the Hit rate for the neural network based forecast, but we have also compared the forecasting efficiency between tenors in a given time period with the Diebold-Mariano test. As the GARCH forecast the latent conditional volatility we could not measure the goodness of fit of this volatility model, thus it was only tested indirectly in trading.

# 8. Results

### 8.1 Forecasting accuracy in different time periods and tenors

In this section we are going to present the results of the model for each time period. Starting with the goodness-of-fit of the forecast we further detail the evolution of forecasting accuracy in different time periods and through different maturity classes. Than we present the trading results for each period and in every maturity class. For measuring performance not only do we apply the annualized return, but we also calculate the risk weighted return of the period with the Sharpe ratio. Moreover we present the associated MSEs and hit rates in line with the profitability measures enabling us to make further inferences on the relation between the profitability and the goodness of fit of the forecast. In each period the results of the corresponding GARCH based trading strategies are listed and by benchmarking the result of the neural network to that of the GARCH a conclusion is drawn on the efficiency of the model. Finally we benchmark the results of the model to that of a buy and hold strategy conducted during the same period with the S&P 500 index, thus putting the result of this article into larger perspective.

Taking a closer look on the average mean square error values of the forecast for each period we detect an increasing trend as the average number of days to maturity rise *(Table. 3.).* Apparently the longer the maturity of the option the less reliable the estimate provided by the forecasting model for the future value of the volatility.

| Mean Square Errors for volatility forecasting with ANN | | | |
|---|---|---|---|
| **Period/Maturity class** | **1st class** | **2nd class** | **3rd class** |
| **2007-2009** | **0,005450** | **0,002372** | **0,004476** |
| **2011-2013** | **0,000464** | **0,000484** | **0,002996** |
| **2014-2015** | **0,000476** | **0,000370** | **0,001458** |

*Table 3. Mean Square errors for volatility forecasting (source: own editing)*

Quite understandably in higher tenors future expectations on the price of the underlying are more heterogeneous and relies on several factor. Regarding the vertical dimension of the table we note a decreasing trend between the error measures of the first and the following periods. Although volatility trading deemed profitable in late 2009 it could not have offset the impact the huge losses incurred towards the end of 2008 and early 2009, hence the higher value for 2007-2009. The forecasting accuracy in the second period (2011-2013) is not as high as in the third period. However if we compare the MSE values of the first tenors to those of the second we note that contradicting the previously observed decreasing trend the error measures of the first maturity class are considerably lowers than those for the second. Consequently we expect the level of profitability from 2007-2009 to 2011-2013 to fall, but not at such extent, as it should from one maturity class to the other.

| Hit rate for volatility forecasting with ANN | | | |
|---|---|---|---|
| **Period/Maturity class** | **1st class** | **2nd class** | **3rd class** |
| **2007-2009** | **49,17%** | **51,67%** | **52,50%** |
| **2011-2013** | **55,83%** | **58,33%** | **53,33%** |
| **2014-2015** | **48,33%** | **50,00%** | **50,83%** |

*Table 4. Hit rates for volatility forecasting (source: own editing)*

Another indicator of forecasting accuracy is the hit rate, which is the ratio of correctly guessed movements of the future volatility. Given that the straddle trading relies heavily on the directional forecast grabbed by the hit rate, this indicator plays an even greater role in profitability than the actual deviance of the forecast from the "true" value, portrayed by the MSE. Based on the table above it can be concluded that the model as whole produces hit rate values around 55%, thus it generally has reasonable accuracy *(Table 4)*. However this accuracy varies within different time periods and maturity classes. The first time period (2007-2009) shows weak results, with the hit rate falling below 50% in the first maturity class and just balancing slightly over it in other tenors. This may largely due to the turbulence of late 2008, where the model was not able to produce reliable estimates. Quite reasonably the inability of the network to predict future volatility is mainly apparent in the first maturity class, as the investor's expectation regarding short term implied volatility was heavily affected by the financial turmoil and inconsequence time series of implied volatility was characterized with sudden jumps, structural breaks and movements never have seen before. The directional accuracy have slightly improved in the second and third period, but as the corresponding high MSE values have shown the forecasting ability of the model remained poor in the period of 2007-2009. The following period shows higher hit rate accuracies around 53%-58% reaching its local maxima in the second maturity class and shrinking moderately to the third. In 2014-2015 hit rate accuracy is generally lower than in the previous period in all maturity classes with its level falling even below 50% in the first maturity class. In section 8.2 we further elaborate on the possible causes of the deterioration of the model in this time period.

Before moving on to the presentation of the trading results we analyze the change in the level of forecasting accuracy as we trade options with longer time to maturities on a sample from 2012 *(Fig 8, 9, 10)*. In the first maturity class the figure shows that the forecasted volatility (red line) approximates the actual volatility in the same tenor (blue line) with high precision *(Fig. 8.)*. The corresponding hit rate accuracy is shown with dots on the bottom of the figure, with 1 meaning the correctly guessed and -1 the missed individual forecasts.

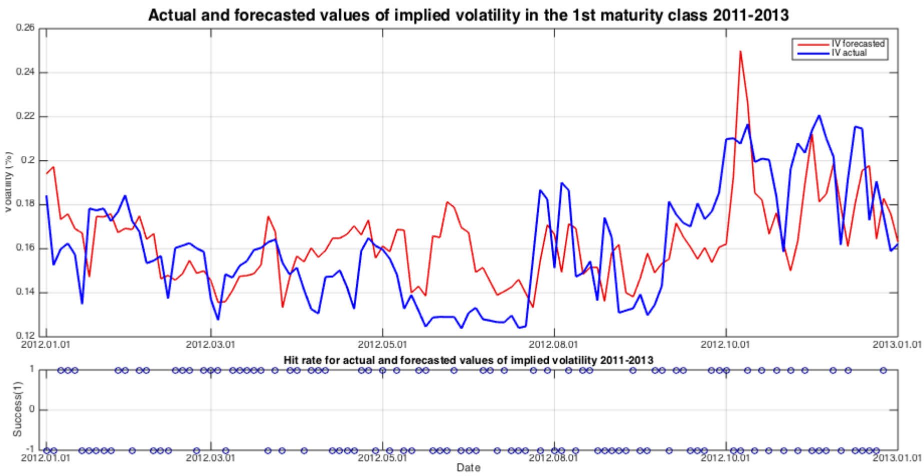


*Figure 8. Forecasting accuracy and hit rate in the first maturity class in 2012 (source: own editing)*

Even though the forecasted values in the second maturity class (red line) estimate the trend of the actual volatility well (blue line) they cannot correctly reflect the detailed fluctuation of the implied volatility, specifically in the first quarter of the year *(Fig. 9.)*. If we compare the MSE values for the two forecasting series we find that the one for the second tenor is not significantly higher compared to that of the first one.

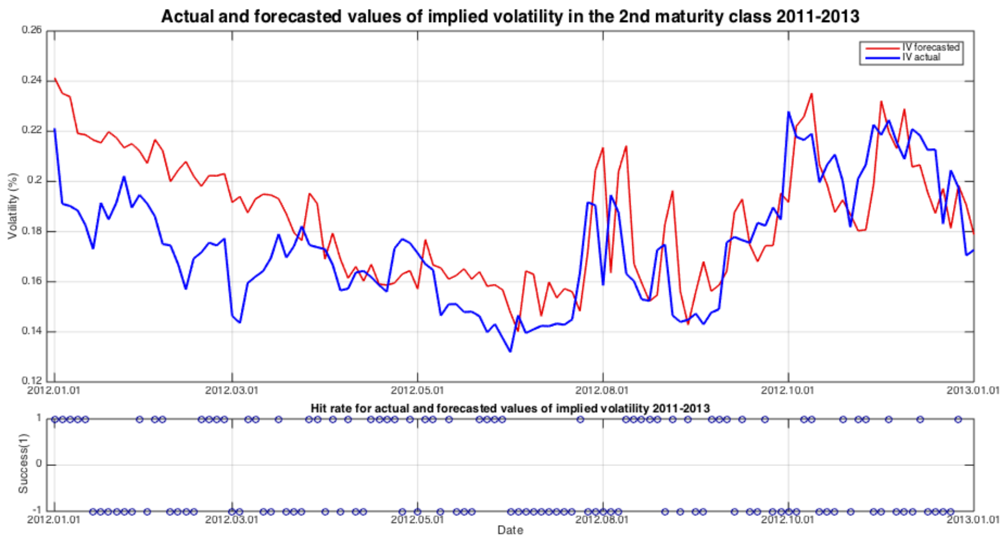


*Figure 9. Forecasting accuracy in the second maturity class in 2012 (source: own editing)*

In order to verify the observation that the forecasting accuracy in the second tenor is smaller we have run the Diebold-Mariano statistical test introduced and detailed in section 7.1. The critical values for the test were 0,2505 so in every usual confidence level 95%, 99% we accept the null hypothesis that the loss difference is zero and the two forecast has equal forecasting accuracy. The hit rate of correctly guessed volatility movements for the second period slightly exceeds that for the first period and result in higher profits in this section of the option market.

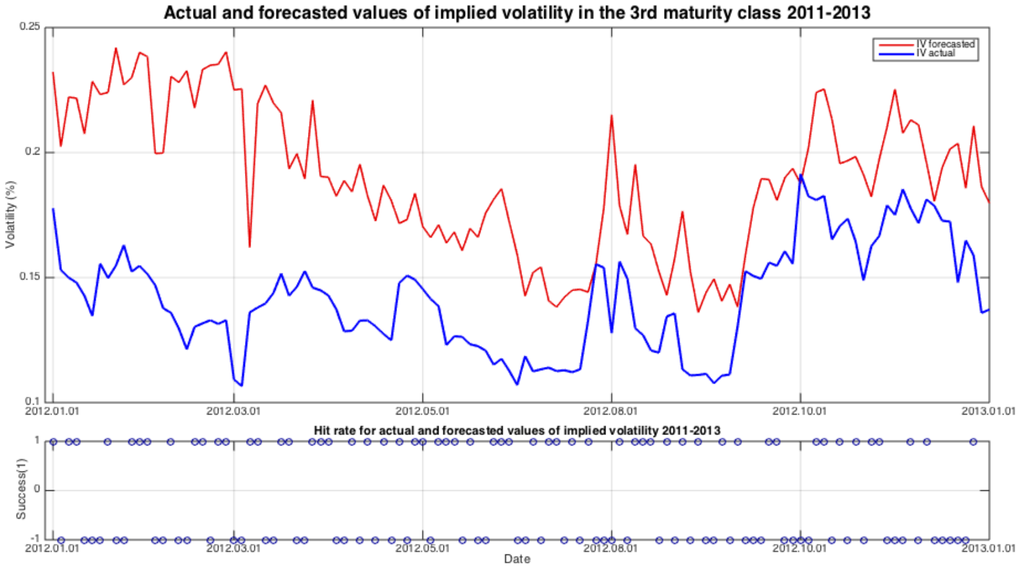


*Figure 10. Forecasting accuracy in the third maturity class in 2012 (source: own editing)*

Slightly different observations can be drawn from the corresponding figure for the third maturity class where the forecasted values (red line) seemingly co-move with the actual volatility (red line) during the whole period, but not only do the forecasted time series completely fails to capture the fluctuation and small changes in the series of the target volatility, but it also consistently overestimates the level of volatility (Fig. 10.). In accordance with the previous observation Hit rate for this segment of option market decreases significantly, which in turn will result in losses detailed in section 8.2. The MSE value increases with almost 600% from the previous maturity classes providing further evidence for the deterioration of forecasting accuracy. *(Table 3.).* We have also examined whether the forecasting errors of the third and the other two maturity classes are equivalent just to make sure that and found that the null hypothesis of similar errors can be rejected with huge DM statistic values (-9,81 and -8,397).

The figures for forecasting accuracy and hit rates for the period 2007-2009 *(Figures 16, 17, 18)* and period 2014-2015 *(Figures 19, 20, 21)* are presented in the appendix.

All in all there is no linear relationship between the decrease of forecasting accuracy and the time to maturity of the options traded. As the hit rates and MSE values show the forecasting power in the second maturity class generally over perform that in the first tenor *(Table 3 and 4)*. Moving on to the trading result we present further results on the profitability of trading in each maturity class and draw the conclusion on the relation between the accuracy and amount of profit generated.

## 8.2 Trading results

A trading simulation detailed in section 7.2 has been conducted in each time period and maturity classes. In this section we are going to present the result of the research by first analyzing the summary tables of trading results for each period. Apart from returns and Sharpe ratios we list the corresponding mean square errors and hit ratios to connect the forecasting accuracy with the profitability. Results are presented for each time period in chronological order and profitability of each tenor is further analyzed in the second time period.

The following table summarizes the profits and losses for the period of 2007-2009 *(Table 5.)*. Due to extreme market environment of late 2008's and early 2009's the period as a whole shows large-scale losses in all maturity classes. The corresponding Sharpe ratios reflect the market stress and the huge standard deviation of the returns appropriately.

| Trading results, Sharpe ratios, MSE-s and Hit rates 2007-2009 | | | | | | |
|---|---|---|---|---|---|---|
| Maturity | *1st class* | | *2nd class* | | *3rd class* | |
| class | ANN | GARCH | ANN | GARCH | ANN | GARCH |
| **Return (%)** | ***-69,70%*** | *-97,90%* | ***42,25%*** | *-44,57%* | ***-79,65%*** | *-39,88%* |
| **Sharpe** | ***-4,81*** | *-6,08* | ***3,50*** | *-3,51* | ***-5,01*** | *-3,14* |
| **MSE** | 0,005450 | | 0,002372 | | 0,004476 | |
| **Hit rate (%)** | 49% | | 52% | | 53% | |

*Table 5. Trading results, Sharpe ratios and MSE-s 2007-2009 (source: own editing)*

A negative relationship is detected between the mean square error and the returns, but the losses are bigger in the third class than in the first despite of its smaller MSE value. Profit could only be generated when we engaged in trading options with 2 months maturity. One possible explanation for that is that overreaction of investors, fear and fire selling to bad news materialize in the price of options with 1-month maturity and has smaller impact on options with longer maturities.

The benchmark GARCH-based strategy generates losses in all segment of the option market examined in this paper. The higher the time to maturity the smaller the loss incurred when trading strategy is based on the GARCH model. The result suggests that the GARCH, which forecast the conditional volatility, is unable to capture the sudden and structural changes in the time series of implied volatility, hence the losses in all segments. If we take a look at the forecasting accuracy of the model in the first option class the hit rate of the model shamefully fall below 50% producing more incorrect than correct guesses on the direction of the future volatility and thus proves to be inadequate. Despite of the fact that the hit rate strengthens back to 52-53% huge losses still occur in the third maturity class. All in all the performance of the model is very poor in this time period, but as the benchmark GARCH model and the general market environment produces similar losses we can not properly evaluate its validity. Plots on the profitability of the ANN and GARCH based strategies for the period of 207-2009 can be found in the appendix *(Figures 22,23,24)*.

The following time period from 2011 to 2013 shows more promising results as large amount of profits are achieved in all the three segment of the option market *(Table 6.)*. Although the level of profit is declining as we trade options with longer time to maturity, an impressive 53% return can be reached even in the third tenor. The corresponding high Sharpe ratios (6.92, 3.76, 3.08) also demonstrate the power of the trading strategy as portfolios with Sharpe ratio values above 2 are considered as excellent investment opportunities.

| Trading results Sharpe ratios and MSE-s 2011-2013 | | | | | | |
|---|---|---|---|---|---|---|
| | ***1st class*** | | ***2nd class*** | | ***3rd class*** | |
| Maturity class | ANN | GARCH | ANN | GARCH | ANN | GARCH |
| **Return (%)** | ***128,09%*** | *-39,84%* | ***60,63%*** | *-49,97%* | ***52,62%*** | *-46,44%* |
| **Sharpe** | ***6,92*** | *-3,31* | ***3,76*** | *-5,78* | ***3,08*** | *-4,14* |
| **MSE** | 0,000464 | | 0,000484 | | 0,002996 | |
| **Hit rate (%)** | 56% | | 58% | | 53% | |

*Table 6. Trading results Sharpe ratios and MSE-s 2011-2013 (source: own editing)*

This period also shows a positive relationship between the annual profits achieved and the goodness-of-fit of the volatility forecast, given that as MSE values increase the profitability of the model diminishes markedly. We must note that even though that the Diebold Mariano test judged the forecasting accuracy of the model in the first and second class equal detailed in section 8.1, profits are almost twice as high in the former period undermining the equivalence of forecasting accuracy and profitability and questioning the causality between the goodness of fit of the forecast and the trading results.

The benchmark GARCH model produced huge losses in every maturity class throughout the whole period lagging behind the results of our models. Generally despite of the fact that both the European debt crisis and the US debt ceiling crisis took place during this period the model performed considerably well. This might actually be attributed to the general observation that volatility trading tends to be more profitable closely following periods of market stress.

Moving on to the figures on the profitability of the three maturity classes we can find the plot of portfolio values for both the neural network based and the GARCH based agent in the upper part of the figure. Below this plot we graphed the time series of the change in the implied volatility mainly to demonstrate the impact of volatility on the profitability of the model (Figure 11).

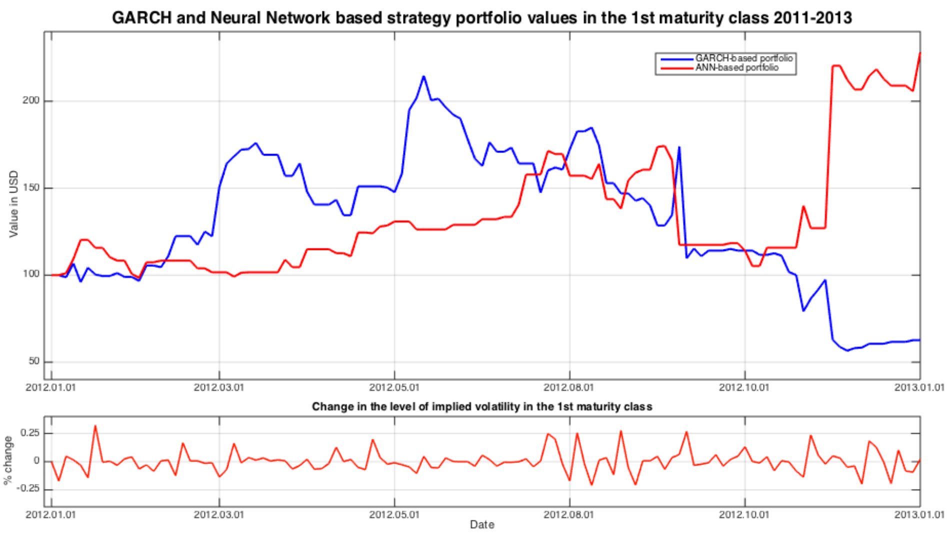


*Figure 11. Profitability of ANN and GARCH based strategies in the 1st maturity class 2011-2013 (source: own editing)*

The figure above presents these features for the first maturity class in 2011-2013 with the red line representing the proceeds of the neural network and the blue line those of the GARCH portfolio. The ANN based portfolio value is increasing steadily with infrequent jumps, the timing of which largely correlate with a similar change in the level of implied volatility. The ANN-based portfolio show huge profits towards the end of the year, while the GARCH-based decrease markedly almost halving its initial value by December. The jumps in the value of ANN-based portfolio correlate with large-scale movements in the time series of volatility.

Portfolio values in the second maturity class show less impressive results. Jumps and large movements coincide with those in the time series of the implied volatility and we can also observe the beneficial effect of the filters in the ANN portfolio value of not letting the model trade in every day. The benchmark GARCH model produce large jumps and generates significant losses towards the end of the period.

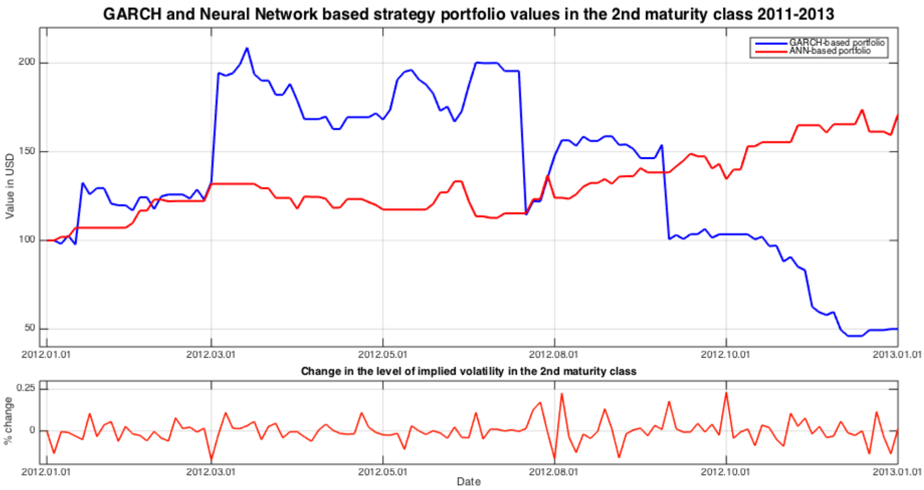


*Figure 12. Profitability of ANN and GARCH based strategies in the 2nd maturity class 2011-2013 (source: own editing)*

Profitability in the third maturity class is similar to that in the second tenor. The ANN portfolio grows in value and reacts to the jumps and movements in the underlying volatility, while the fluctuation in the volatility heavily affects the GARCH portfolio value towards the end of the year. All in all the model based trading beats the GARCH based benchmark consistently throughout the whole period and generates two digit returns *(Table 6.)*.

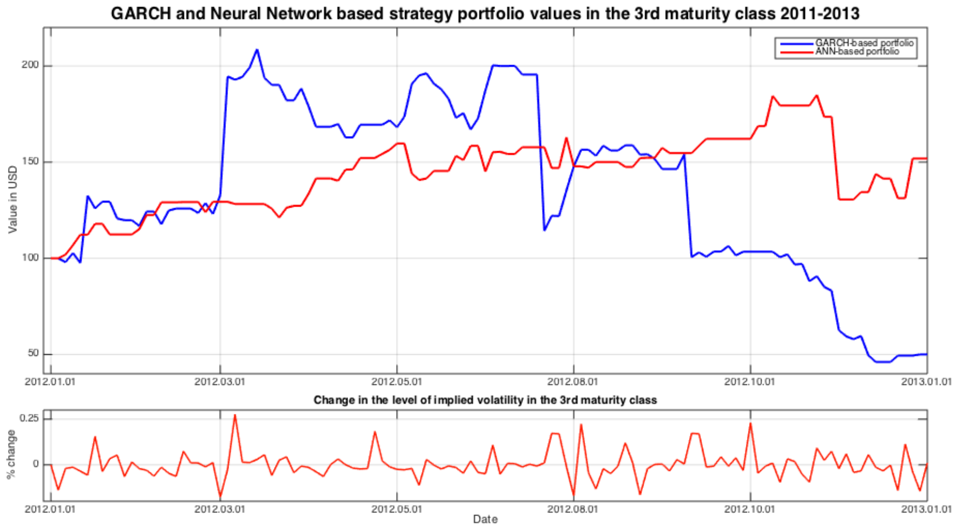


*Figure 13. Profitability of ANN and GARCH based strategies in the 3rd maturity class 2011-2013 (source: own editing)*

The last and most recent set of observation from 2014-2015 show distinctly different results compared to those of the previous period, even though forecasting accuracy in each maturity class is similar to those in the 2011-2013 period *(Table 6.)*.

| Trading results, Sharpe ratios, MSE-s and Hit rates 2014-2015 | | | | | | |
|---|---|---|---|---|---|---|
| | *1st class* | | *2nd class* | | *3rd class* | |
| Maturity class | ANN | GARCH | ANN | GARCH | ANN | GARCH |
| **Return (%)** | ***-41,57%*** | *-97,50%* | ***-35,00%*** | *-5,00%* | ***-25,00%*** | *-10,00%* |
| **Sharpe** | ***-3,96*** | *-8,06* | ***-3,56*** | *-0,54* | ***-3,77*** | *-1,15* |
| **MSE** | 0,000476 | | 0,000370 | | 0,001458 | |
| **Hit rate (%)** | 48% | | 50% | | 51% | |

*Table 7. Trading results Sharpe ratios and MSE-s 2014-2015 (source: own editing)*

Once again the hit rate fells below 50% in the first maturity class creating a major deficiency in the model. Despite of the fact that the MSE has not increased significantly between the two periods large amount of losses were generated in this period as opposed to the double digit profits in the period of 2011-2013. Losses coupled with low hit rates kept appearing in every maturity class undermining the general validity of the model. Although losses decrease as we trade with options with higher maturity they are still pose a systematic problem. To examine this irregularity we examine the portfolio values of the model and GARCH portfolios trading in the 1st maturity class during this period *(Figure 14)*. The figure shows that despite a promising start until the first quarter of the year the model simply can't benefit from the changes in the volatility and steadily looses the initial investment over time. Even more alarmingly the same patter appears in the other maturities *(Figure. 25 and 26)*.

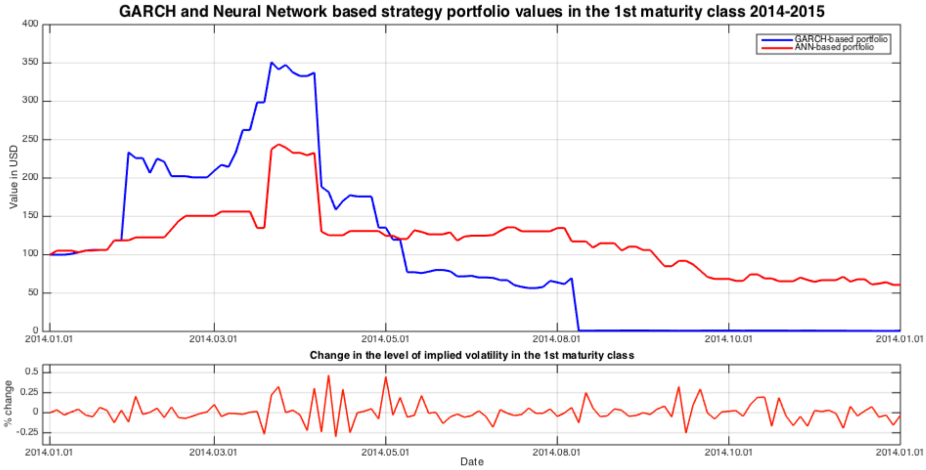


*Figure 14. Profitability of ANN and GARCH based strategies in the 1st maturity class 2014-2015 (source: own editing)*

There are several explanations for this phenomenon. First and the most obviously the period of 2014-2015 is simply not that turbulent that extra profit could be generated from directional volatility trading. In the majority of trading days change in volatility either remains below the filter or after taking into account transaction costs deems unprofitable to trade as incurring costs absorb the profits and slowly decay the invested capital. Several market indicators point into this direction. The value of VIX index has fallen more than 50% from mid 2012 to mid 2014 showing a significant decrease in the general level of volatility and uncertainty. Moreover he characteristics of the slowly decaying portfolio value also provide a support for this theory. On the other hand it is equally possible that the market has "learnt" the results of the model, meaning that the current price of the options observed on the markets is already incorporated the mispricing and no further extra profits can be achieved by applying a neural network for forecasting the volatility. The low MSE values and the unresolved difference in profitability compared to the corresponding maturities in the previous time period provide support for this suspicion. In order to verify our observations and reach a reassuring conclusion further simulation of trading is needed in a late 2015-2016 time period.

Finally putting the result of the model into a bigger perspective we have simulated a buy and hold strategy with the S&P 500 index for the corresponding time spans in each period *(Table 7.)*. The results were as follows.

| Trading profits of the best case model and the S&P 500 B&H strategy | | |
|---|---|---|
| Period/ Model | Model profit | S&P 500 Buy& Hold |
| **2007-2009** | *42,25%* | *-10,90%* |
| **2011-2013** | *128,09%* | *17,63%* |
| **2014-2015** | *-25,00%* | *2,50%* |

*Table 8. Trading profits for ANN and market benchmark strategy (source: own editing)*

By comparing the results of the trading based on our model and the one of a buy and hold strategy on the underlying index we can conclude that the former generated higher profits than the latter. It is important to note however that the table represents the "best case scenario" meaning that we presented the highest return the model can generate in the given time period. The result suggests the from 2009 to 2013 the option trading framework based on the prediction of an artificial neural network and enhanced by an EGARCH outshines the buy and hold strategy on the underlying index.

In order to get a broader view on the profitability of the trading strategy its sensitivity to the level of the filter on volatility and of the transaction cost should also be analyzed. We have therefore conducted a sensitivity analysis on the portfolio value by changing the volatility filter on the 0%-4% and the transaction cost on the 0%-3% grid. Profits have reached as high as 650% by setting both the transaction cost and the filter at the artificial level of 0%. Profits have sharply declined as the transaction cost was increased to 1% and diminished completely when the level of cost exceeded 1,5%.

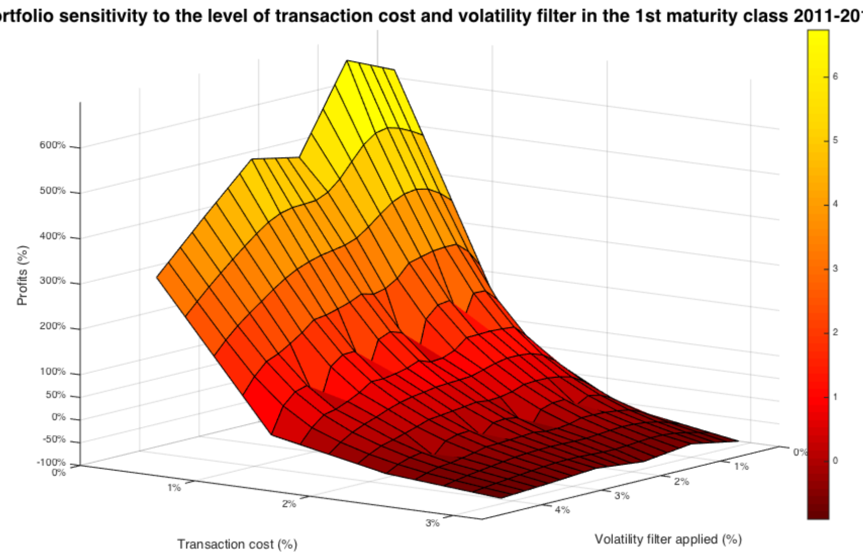


*Figure 15. Sensitivity of the portfolio value to transaction costs and volatility filters (source: own editing)*

An increase in the level of volatility filter also had a similar negative impact on profits, but not at such extent as the transaction cost and in some cases the effect reversed and by increasing the level of filter even more profits were generated. This would mainly be due to the beneficial effect of filter that it prevents small-scale trades and reduces unnecessary transaction costs. It is clearly visible on the upper regions of the surface that profit increase steadily until the level of filter reaches 1% and than decreases rapidly until the 2% level just to start increase again until 3 % level. Seemingly the returns are distributed in a way that 1% filter maximizes the profits and by increasing the limit for change in the volatility we reduce the profits. If however the level of filter is set at 3% large amount of small-scale, cost generating trades disappear and the profitability increases once again.

## 9. Conclusion

In the past sections we have presented an integrated multicomponent model to forecast volatility and then values to build a successful option straddle trading strategy relying on the forecasted values. Following the brief introduction of the topic and the hypotheses we have moved on to detail the various methods of volatility forecasting paying special attention to neural networks and their application in estimating the future volatility. Furthermore we detailed the advantages and drawbacks of the Black-Scholes option-pricing model offering a possible enhancement of the model through hybridization with neural networks. Then we have elaborated on the topic of volatility trading by providing of a summary of recent research on the topic. In the second part of the paper we have proposed a multicomponent model to forecast volatility and trade options incorporating all the features detailed in the first part. The remaining of the paper described the model by first detailing the data preprocessing and the estimation of input variables and later giving an account on the mechanism of the model. The results are presented and analyzed in the last part of the paper.

At the beginning of the article we have established three hypotheses that are yet to be proved. The first hypothesis was that the Artificial Neural Network provides a more accurate volatility forecast than does the GARCH model. As trading results in section 8.2 showed the trading strategy relying on the neural network outperform that of using the GARCH model forecasts in almost all time periods and maturity classes.

The second hypothesis stated that abnormal profits could be gained by feeding the forecasted future volatility into a trading strategy even after taking transaction costs into account. As demonstrated in the trading results abnormal profits did occur in the second and in some cases in the first time period taking into account the 1% transaction cost. Consequently should the 1% level correctly model the transaction cost the option market was inefficient in certain periods from 2009 to 2013, but this inefficiency seemed to have disappeared by mid 2014 resulting in slowly decaying portfolio values and the inefficiency of the model.

The third and last hypothesis assumed that options with different time to maturity reacts differently to the forecast of volatility, thus the level of profitability achieved differs in every segment of the option market. We have demonstrated in section 8.1, that the forecasting accuracy of the model changes with the increase of average time to maturity, forecasts for the second maturity class were better than for the first maturity class in most cases. Not only did we justify the hypothesis with the change in the MSE values, but also with the different levels of profitability incurring in each maturity class. Profits shrank and even turned to losses as the average time to maturity of traded options has risen to 90 days. Therefore we can conclude that the model shows superior explanatory power compared to that of the GARCH model and the trading results in different levels of profitability in each maturity classes, which can also be regarded as different segment of the option market. Finally the losses incurring in 2014-2015 provide evidence for the assumption that on its own providing a forecast with an acceptable level of goodness-of-fit does not necessarily lead to abnormal profits and that the market environment has a huge impact on the profitability of the trading strategy. Furthermore the this observation reflects upon the dilemma of the useful lifetime of an integrated forecasting an trading model, as to how long can we reach abnormal profits with a specific strategy before the market learns and applies its rules and force us to look for new more promising models.

In order to build the model and perform the analysis within the given model framework a few limitations had to be introduced. Firstly the trading simulation lacks stop-loss limit that would define the distribution of possible gain and loss incurring in every trade cycle. Secondly transaction cost is set at 1% level, which shows the difference between the models and is useful assumption for ranking and classifying, but might not actually cover the bid ask spread applied by the market. We could either trade with bid and ask prices instead of mid or set the level of transaction cost to absorb bid-ask spread.

In the future we are planning to further extent the boundaries of the research towards several directions. The first goal would be to take into account the bid-ask prices and create a model that alters standard assumptions and trades not on daily bases, but on higher frequencies using intra-day data.

Another interesting direction would be the inclusion of in-the money and out-the money call and put prices. Should we feed the model with price, implied volatility or other features derived from these options we might increase profitability or even trade with options with other maturities. Not less intriguing question is the implied volatility of options with maturities less than 15 days. These options produce sudden movements and jumps and reflect the liquidity of the market as well the short expectations of market participants'. The additional information derived from these assets might serve as additional input node to any option-pricing model accounting for sudden shocks. We might as well turn our attention to intraday prices of options and by applying machine learning techniques establish trading strategy at that frequency of the market. Trading with options for individual stocks, instead of indexes is also an interesting field for further research. More volatile, but liquid stock options such as the options for Apple, Tesla or other tech firms might prove to be even more profitable in trading. It would also be interesting to apply the model to currency options. By providing huge amount of liquidity currency options are suspected to be more efficient on daily basis, but temporary inefficiencies might be found examining intra-day data.

In terms of methodology a plausible extension of this research would be to include Support Vector Machine or other machine learning technique and its comparison with neural networks. We are expecting to find similar level of forecasting ability in terms of MSE, but different level in the profitability of corresponding trading strategy.

The novelty of this paper lies in the followings. Although many have forecasted both implied and realized volatility using different methods few have proved its effectiveness by establishing an option trading strategy. The article is the first to compare the profitability levels of trading with option in different tenors. The results have confirmed that options in higher maturity classes tend to underperform those in lower tenors. Secondly a few scholars have examined the impact of market calm and stress to the accuracy of forecast in terms of error measures. This paper examines the impact of different economic environments to the level of profitability not by comparing the error measure, but also by conducting a trading simulation. The results have shown that although change in the error measures negatively correlate with the profitability in general, in the periods of market stress the relative accuracy of the forecast doesn't have an impact on the profitability of the strategy.

Finally as most of the research on option trading worked with pre-crises data, the article is a pioneer in researching on post-crises dataset spanning from 2011 to 2015. Hopefully, the result of this paper will spur others to conduct further research on the topic and on the efficiency of the option market.

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## List of Figures and Tables

***Figures***



***Tables***

## Appendix 1: Figures

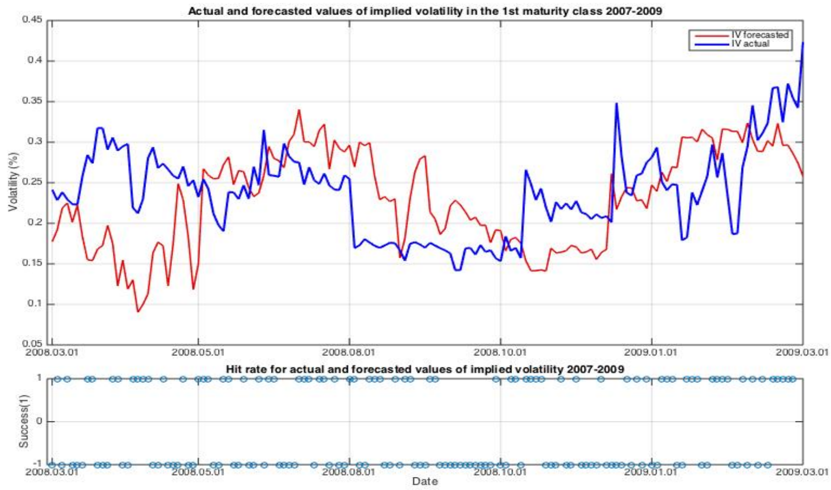


*Figure 16. Forecasting accuracy in the first maturity class in 2007-2009*

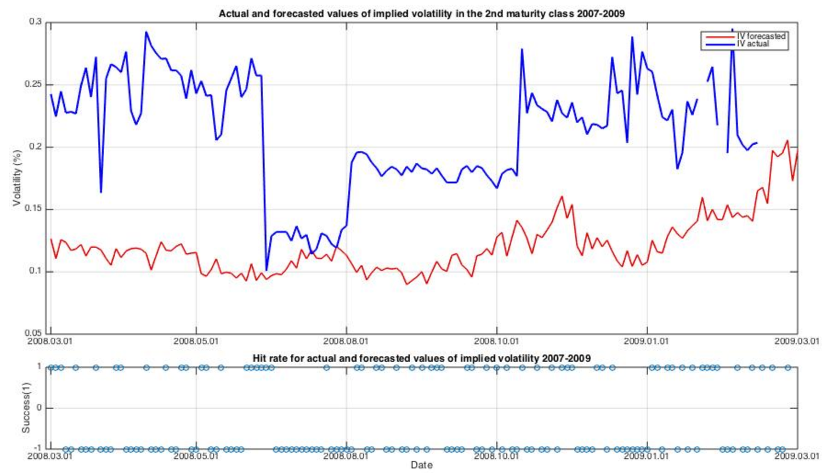


*Figure 17. Forecasting accuracy in the second maturity class in 2007-2009*

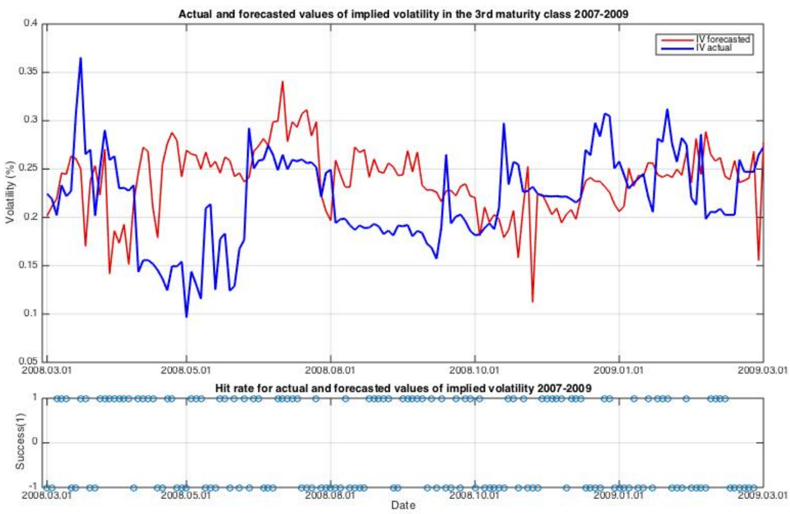


*Figure 18. Forecasting accuracy in the third maturity class in 2007-2009*

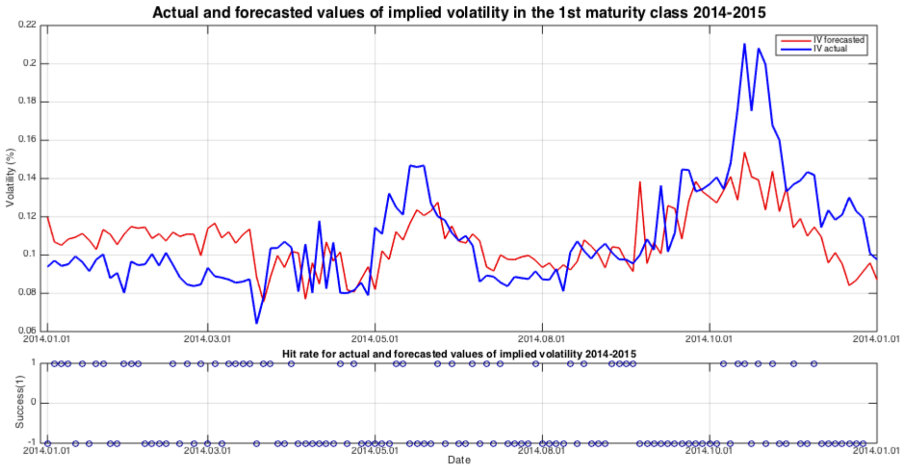


*Figure 19. Forecasting accuracy in the first maturity class in 2014-2015*

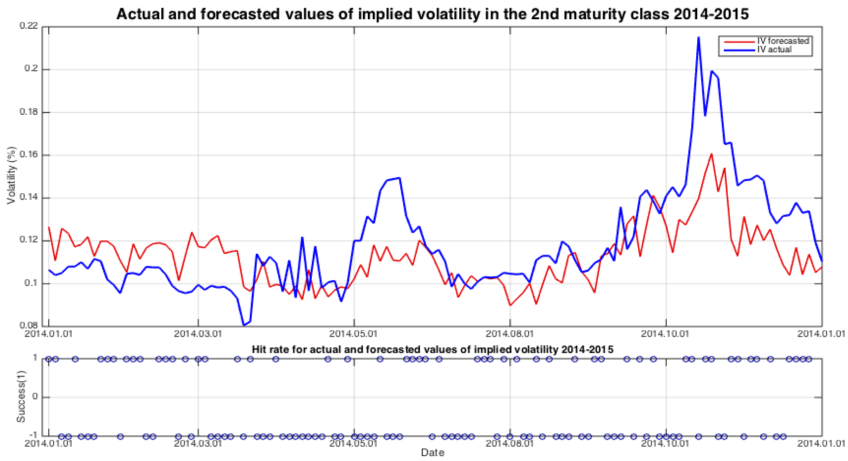


*Figure 20. Forecasting accuracy in the second maturity class in 2014-2015*

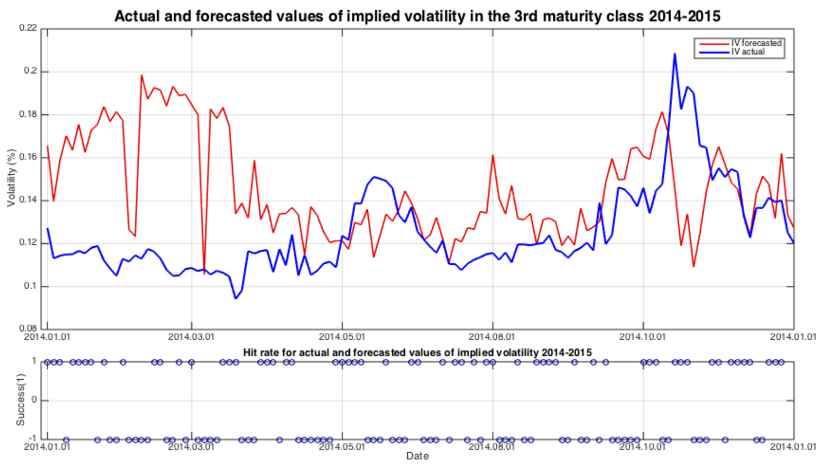


*Figure 21. Forecasting accuracy in the third maturity class in 2014-2015*

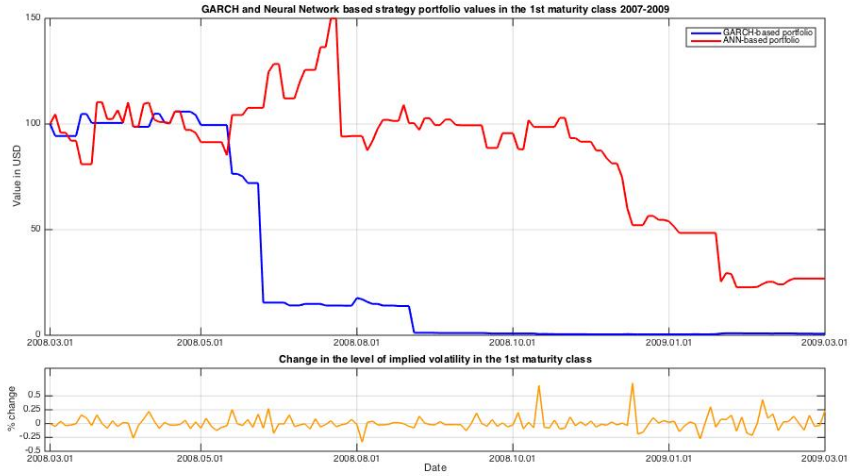


*Figure 22. Profitability of ANN and GARCH based strategies in 2008-9 (1st class)*

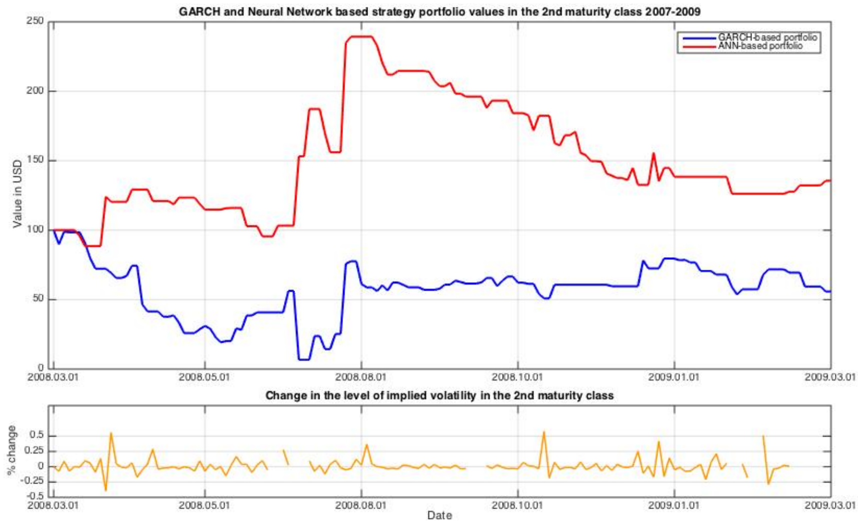


*Figure 23. Profitability of ANN and GARCH based strategies in 2008-9 (2ndt class)*

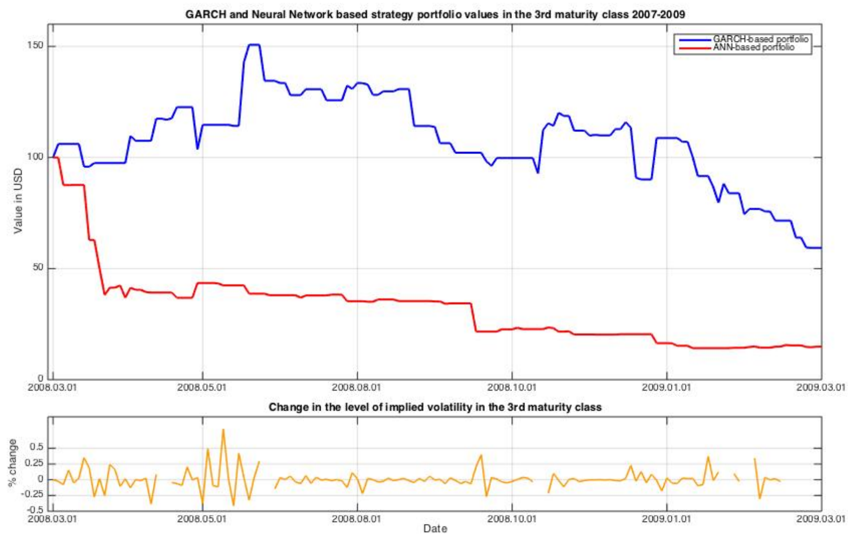


*Figure 24. Profitability of ANN and GARCH based strategies in 2008-9 (3rd class)*

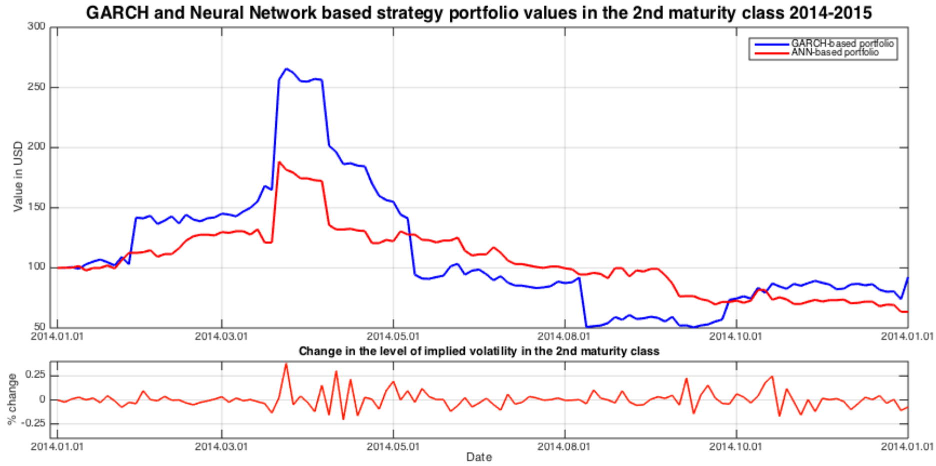


*Figure 25. Profitability of ANN and GARCH based strategies in 2014 (2ndt class)*

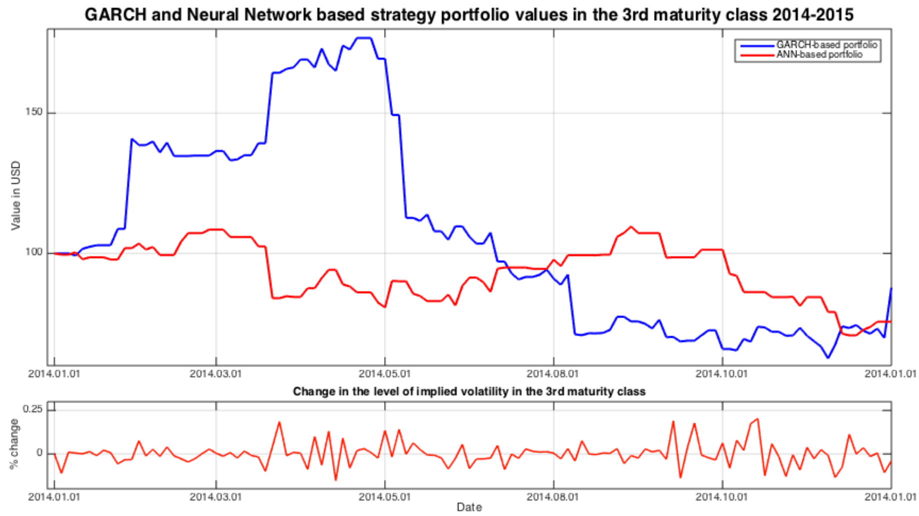


*Figure 26. Profitability of ANN and GARCH based strategies in 2014 (3rd class)*

# Appendix 2: Codes

## 1. Volatility modeling in R, specifying and fitting an ARMA(p,q)-GARCH(p,i, q) and EGARCH(P,Q) models

```
######################Modeling ARMA(p,q) - EGARCH() models #################################
####################################################################################

#Downloading data from Yahoo Finance - S&P 500
        library('quantmod')
        getSymbols("^GSPC", from ="2007-06-30", to = "2015-09-29")
        data.ts <- GSPC
        chartSeries(Ad(data.ts))
        colnames(data.ts)
        start(data.ts)
        end(data.ts)

#Data preprocessing and calculating returns
        data.ts = data.ts[, 6, drop=F]
        plot(data.ts)
        head(data.ts)
        data.ret = dailyReturn(Ad(data.ts), type='log')

#Creating subsamples, indexing depends on the size of the sample
        Period1_ret<- data.ret[150:450]
        Period2_ret<- data.ret[700:950]
        Period3_ret<- data.ret[950:1250]

#Fitting the adequate ARMA model to the mean equation for every subsample
        install.library('forecast')
        library('forecast')
        Period1_ARMA_fit <- auto.arima(Period1_ret, max.p=3, max.q=3, ic=c("aic"))
        Period2_ARMA_fit <- auto.arima(Period2_ret, max.p=3, max.q=3, ic=c("aic"))
        Period3_ARMA_fit <- auto.arima(Period3_ret, max.p=3, max.q=3, ic=c("aic"))

#Testing residuals /period needs to be changed
        res_SPX<-Period1_ARMA_fit$residuals
        res2_SPX<-res_SPX^2; plot(res2_SPX)
        Box.test(res2_SPX, type="Ljung-Box", lag = 10)
        library("FinTS")
        ArchTest(res2_SPX)

#Specify and fit an adequate rolling GARCH model for each subperiod
# Given the rolling characteristic of the model only the number of corresponding
# mean equation parameters need to be substituted into the equation
        library('rugarch')
        garch11.spec = ugarchspec(variance.model = list(garchOrder=c(1,1)),
                       mean.model = list(armaOrder=c(0,2)))

        SPX.garch11.roll = ugarchroll(garch11.spec, Period1_ret, n.ahead=1,
                        forecast.length = 250,
                        refit.every=21, refit.window="moving")

# Checking goodness-of-fit of the model
        data.garch11.fit

# Plotting and saving conditional volatility of the GARCH model
        condvolrollgarch11<-SPX.garch11.roll@forecast$density
        plot(SPX.garch11.roll@forecast$density$Sigma[500:1000], type='l', col='red')
        sigma=as.data.frame(SPX.garch11.roll,which="sigma")
        plot(sigma)

        mentes2 <- condvolrollgarch11
        write.csv(mentes2, "garch11_roll.csv")

# Specifying and fitting an EGARCH model rolling method armaorder must be altered
        egarch11.spec = ugarchspec(variance.model = list(model="eGARCH", garchOrder=c(1,1)),
                        mean.model = list(armaOrder=c(0,2)))

        SPX.egarch11.roll = ugarchroll(egarch11.spec, Period1_ret, n.ahead=1,
                         forecast.length = 250,
                         refit.every=21, refit.window="moving")
```

```
# Checking goodness-of-fit of the model
        data.egarch11.fit

# Plotting and saving conditional volatility of the GARCH model
        condvolrollegarch11<-SPX.egarch11.roll@forecast$density
        plot(condvolrollegarch11$Sigma, type='l', col='red')
        mentes2 <- condvolrollegarch11
        write.csv(mentes2, "egarch11_roll.csv")

#######################################################################################
```

## 2. Visual Basic for Application codes: Implied volatility estimation and Newton_Raphson method

```
# The function prices the European call or put option based on the Black-Scholes differential equation with Strike price, Excercise price, volatility, risk free rate, Time to maturity and dividend rate  as input variables.

Function EuropeanOption(CallOrPut, S, k, v, r, T, q)
Dim d1 As Double, d2 As Double, nd1 As Double, nd2 As Double
Dim nnd1 As Double, nnd2 As Double

  d1 = (Log(S / k) + (r - q + 0.5 * v ^ 2) * T) / (v * Sqr(T))
  d2 = (Log(S / k) + (r - q - 0.5 * v ^ 2) * T) / (v * Sqr(T))
  nd1 = Application.NormSDist(d1)
  nd2 = Application.NormSDist(d2)
  nnd1 = Application.NormSDist(-d1)
  nnd2 = Application.NormSDist(-d2)

    If CallOrPut = "Call" Then
      EuropeanOption = S * Exp(-q * T) * nd1 - k * Exp(-r * T) * nd2
    Else
      EuropeanOption = -S * Exp(-q * T) * nnd1 + k * Exp(-r * T) * nnd2
    End If
End Function

# The function uses the Newton-Raphson iteration to give an estimate to the volatility of the option

Function ImpliedVolatility(CallOrPut, S, k, r, T, q, OptionValue, guess)
  Dim epsilon As Double, dVol As Double, vol_1 As Double
  Dim I As Integer, maxIter As Integer, Value_1 As Double, vol_2 As Double
  Dim Value_2 As Double, dx As Double

  dVol = 1e-05
  epsilon = 1e-05
  maxIter = 100
  vol_1 = guess
  I = 1
    Do
      Value_1 = EuropeanOption(CallOrPut, S, k, vol_1, r, T, q)
      vol_2 = vol_1 - dVol
      Value_2 = EuropeanOption(CallOrPut, S, k, vol_2, r, T, q)
      dx = (Value_2 - Value_1) / dVol
      If Abs(dx) < epsilon Or I = maxIter Then Exit Do
      vol_1 = vol_1 - (OptionValue - Value_1) / dx
      I = I + 1
    Loop
  ImpliedVolatility = vol_1
End Function
```

3. Matlab codes: Multicomponent model codes: volatility forecasting and option trading modules and Diebold-Mariano test

```
%% 1.Volatility Forecasting Module
% The module forecasts the future values of implied volatility averages
% using 13 explanatory variable in 'inputom.csv' file. Data is arranged
% rowwise facilitating the standardization with the target variable in the
% first row.The j loop index must be altered according to the length of the
% number of forecasted days (2nd parameter) and the full length of the time
% series (3rd parameter). The output test variable summarize the forecasted
% volatility in each loop, feeding them to the Vol_fcst variable, which is
% the output of the module.
for j=0:30:240
    [Input, cs]=mapminmax(inputom(2:11,1+j:250+j), -1,1);
    [Target, ts]=mapminmax(inputom(1,1+j:250+j), -1,1);
    iteracio=100;
        for p=16:20
            for k=1:iteracio
                setdemorandstream(491218380+k);
                hiddenLayerSize = p; % p=no. of neurons in hidden layer
                net = fitnet(hiddenLayerSize);

                %Dividing the sample first 60 obsv valid, last 190 training
                net.divideFcn = 'divideind';
                net.divideParam.trainInd = 1:200;
                net.divideParam.valInd   = 201:250;
                net.inputs{1}.processFcns = {};
                net.outputs{2}.processFcns = {};
                net.trainFcn = 'trainlm';
                net.performFcn = 'mse';

                %Training of the network
                [net, tr]=train(net,Input,Target);
                outputs = net(Input);
                Output_summa(k,:)=outputs;

                %MSE calculation, searching for minimal MSE
                Output(k,:)=mapminmax('reverse',outputs,ts);
                performance(k,p-9) = mse(net,Target,outputs);
            end
            hiba=mean(Output_summa(1:100,:)); % average of iterations
            x=mse(net,Target(:,201:250),hiba(:,201:250)); % arrange mse-s in x vector
            Emese(2,p-15)=x/50; %MSE values for all ps
            Emese(1,p-15)=p; % No of neurons in hidden layer
            Atlagvol(p-15,:)=mean(Output(1:100,:)); % vector for validation
        end

            lx=find(Emese(:)==min(Emese(:)));
            [row,col]=ind2sub(size(Emese),lx);
            p2=15+col;

        %respecify network with optimal no of neurons in hidden layer
        for k=1:iteracio
            net_final = fitnet(p2);
            [net_final, tr2]=train(net_final,Input,Target);
            outputs2 = net_final(Input);
        end
      Testadat=inputom(2:11,251+j:280+j);    %Testadat= Test_expl. vars
      Testarget=inputom(1,251+j:280+j);      %Testarget= Test_target var
      Testadat_norm=mapminmax('apply',Testadat,cs); %reverse mapminmax
      for k=1:iteracio
        day_fcst(k,:) = sim(net_final,Testadat_norm); %Apply the specified net
      end
      day_fcst_avg(1,:)=mean(day_fcst(1:100,:));
     %Volatility forecast as output of the
     Output_Test(1+(j/30),:)=mapminmax('reverse',day_fcst_avg,ts);
     % vector of volatility forecast
     Vol_fcst((1+(j)):(30+(j)),1)=Output_Test(1+(j/30),1:30);
     % calculating the mse for the test population in every subsample
     Test_mse(1+(j/30),1)=mse(net,Testarget, Vol_fcst);
end
```

```
%% 2.Option Trading Module
% The module relies on the following inputs: Vol_fcst_call/put, C_mid_o,
%P_mid_o,C_mid_c, P_mid_c, GARCH_fcst. The Vol-fcst is derived from the
% previous module, while the others are external inputs.
% The module first computes the directional change and applies filters to
% avoid unprofitable trading (crit_chng). Than using the option prices the
% module calculates straddle prices for a given date for long and short
% straddle strategy using closing prices form the following day.
% Finally the module simulates trading based on the directional change in
% volatility accounting for filters opening a long(short) straddle position
% should the volatility rise (fall). Portfolio value is also computed for
% GARCH strategy where the directional trading is based on the forecasted
% conditional volatility of the model.
n=length(Vol_fcst_call);
p=120; % Length of trading period
Strdl_o=zeros(n,1);Strdl_c=zeros(n,1); L_straddle=zeros(n,1);
S_straddle=zeros(n,1); Trcost=zeros(n,1);

% 1.Calculate implied volatility from observed prices
 IV_mdl_call=zeros(n,1);IV_mdl_put=zeros(n,1); IV_mdl_average=zeros(n,1);
 dIV_mdl_average=zeros(n,1);dIV_mdl_average(1,1)=0;
 for i=1:n
 IV_mdl_call(i)=blsimpv(S(i),K(i),r(i),Tt(i),C_mid_o(i),0.5,0,[],{'Call'});
 IV_mdl_put(i)=blsimpv(S(i),K(i),r(i),Tt(i),P_mid_o(i),0.5,0,[],{'Put'});
 IV_mdl_average(i,1)=(IV_mdl_put(i)+IV_mdl_call(i))/2;
 end

%Calculate deltaIV_mdl_average
 for i=2:n
     dIV_mdl_average(i,1)=(IV_mdl_average(i,1)/IV_mdl_average(i-1,1))-1;
 end
% 2. Filtering change in volatility and setting transaction costs
Ret_ann_tbl=zeros(5,6);Ret_ann_add_tbl=zeros(5,6);
Ret_GARCH_tbl=zeros(5,6);Ret_GARCH_add_tbl=zeros(5,6);
for k=0:0.001:0.05
for c=0:0.0025:0.01
    % Filters are calculated as follows
    crit_chng=k;
    Filter=zeros(n,1);
    dVOL=zeros(n,1);
    for i=1:1:p
        dVOL(i,1)=(Vol_fcst_call(i+1)/Vol_fcst_call(i))-1;
        if abs(dVOL(i))>crit_chng
            Filter(i,1)=1;
        else
            Filter(i,1)=0;
        end
    end

    %Calculating BS prices for call and put with fcstd volatility for day_t
    C_mid_h=zeros(n,1); P_mid_h=zeros(n,1); Strdl_h=zeros(n,1);
    Wrong_call=zeros(n,1);Wrong_put=zeros(n,1);

    for i=1:n
        [C_mid_h(i,1), Wrong_put(i,1)]=blsprice(S(i),K(i),r(i),Tt(i),Vol_fcst_call(i));
        [Wrong_call(i,1),P_mid_h(i,1)]=blsprice(S(i),K(i),r(i),Tt(i),Vol_fcst_put(i));
        Strdl_h(i,1)=C_mid_h(i,1)+P_mid_h(i,1);
    end

    % Calculate straddle prices for given date
    Init=100; %Initial_value
    Trc=c;
    Profit=zeros(p,1);
    PortfolioV=zeros(p,1);PortfolioV_add=zeros(p,1);
    PortfolioV(1)=100;PortfolioV_add(1)=100;
    GARCH_portfolioV=zeros(n,1); GARCH_portfolioV_add=zeros(n,1);
    GARCH_portfolioV(1)=100;GARCH_portfolioV_add(1)=100;

    for i=1:n
        % Straddle values
        Strdl_o(i,1)=C_mid_o(i,1)+P_mid_o(i,1);
        Strdl_c(i,1)=C_mid_c(i,1)+P_mid_c(i,1);

        % calculate transaction costs for each straddle
        Trcost(i,1)=((Strdl_o(i,1)+Strdl_c(i,1))*Trc);
        % Straddle profit with transaction costs
        S_straddle(i,1)=((-Strdl_o(i,1)+Strdl_c(i,1)-Trcost(i,1))/Strdl_o(i,1));
        L_straddle(i,1)=(((Strdl_o(i,1)-Strdl_c(i,1))-Trcost(i,1))/Strdl_o(i,1));
```

```
    end

% 3. Straddle Trading profit based on hypothetical straddle price decision
    for i=2:p
       if Date_lag(i,1)<3;
        if Strdl_h(i,1)-Strdl_o(i,1)>Trcost(i,1) % market straddle underpriced> buy
                Profit(i,1)=L_straddle(i,1)*Filter(i,1);
            elseif Strdl_o(i,1)-Strdl_h(i,1)>Trcost(i,1) % mrkt strdl overpriced> sell
                Profit(i,1)=S_straddle(i,1)*Filter(i,1);
            else
                Profit(i,1)=0;
        end
       else
          Profit(i,1)=0;
        end
    end

% 4. GARCH Profit calculation
    GARCH_Profit=zeros(p,1); dGARCH_VOL=zeros(p,1);
     %apply k as filter
        for i=2:p
           dGARCH_VOL(i,1)=(GARCH_fcst(i,1)/GARCH_fcst(i-1,1))-1;
                   if dGARCH_VOL(i,1)>k
                       GARCH_Profit(i,1)=L_straddle(i,1);
                   elseif dGARCH_VOL(i,1)<-k
                       GARCH_Profit(i,1)=S_straddle(i,1);
                   else
                       GARCH_Profit(i,1)=0;
           end
           %multiplicative: reinvest previous losses gains
           GARCH_portfolioV(i,1)=GARCH_portfolioV(i-1,1)*(1+GARCH_Profit(i,1));
           %additive:store previous losses gains
           GARCH_portfolioV_add(i,1)=GARCH_portfolioV_add(i-
       1,1)+(100*GARCH_Profit(i,1));
        end

    % Calculating Portfolio Value
    for i=2:p;
        PortfolioV(i,1)=PortfolioV(i-1,1)*(1+Profit(i,1));
        PortfolioV_add(i,1)=PortfolioV_add(i-1,1)+(100*Profit(i,1));
    end

% 5. Profit calculation for both portfolios
        Ret_m=(PortfolioV(p,1)/PortfolioV(1,1))-1;
        Ret_ann=((1+Ret_m)^(250/p))-1;
        Ret_G=mean(GARCH_portfolioV(p,1)/GARCH_portfolioV(1,1))-1;
        Ret_GARCH=((1+Ret_G)^(250/p))-1;

        Ret_m_add=(PortfolioV_add(p,1)/PortfolioV_add(1,1))-1;
        Ret_ann_add=((1+Ret_m_add)^(250/p))-1;
        Ret_G_add=mean(GARCH_portfolioV_add(p,1)/GARCH_portfolioV_add(1,1))-1;
        Ret_GARCH_add=((1+Ret_G_add)^(250/p))-1;

        Rf=mean(r);
        Mean_ret=Profit(1:p,1);
        Sharpe_ANN = sharpe(Mean_ret, Rf);
        Sharpe_ANN;
        Ret_ann_tbl(c*400+1,k*100+1)=Ret_ann;
        Ret_GARCH_tbl(c*400+1,k*100+1)=Ret_GARCH;
        Ret_ann_add_tbl(c*400+1,k*100+1)=Ret_ann_add;
        Ret_GARCH_add_tbl(c*400+1,k*100+1)=Ret_GARCH_add;
end
end

% 1 Multiplicative, 2. Additive models
Ret_GARCH_tbl1=real(Ret_GARCH_tbl); Ret_ann_tbl1=real(Ret_ann_tbl);
Ret_GARCH_tbl2=real(Ret_GARCH_add_tbl); Ret_ann_tbl2=real(Ret_ann_add_tbl);

%% 3. Profit Calculation measures
% In the profit calculation module we calculate several measures statistical
% and financial to evaluate the efficiency of the forecast.
% Apart from the hit rate we calculate the Annualized return for the period
% and the Sharpe ratio for the sub period. We further test whether the
% difference between different performance measures for forecasting are
% statistically significant with the Diebold-Mariano test.
% The module heavily relies on two external functions, the hit_rate_ANN,
% and the dmtest and also requires the vector of implied volatility
% averages (IV_mdl_average) as input.
```

```
% 1. Hit rate calculation
        n=length(PortfolioV);Vol_fcst_avg=zeros(n,1);
        for i=1:n
            Vol_fcst_avg(i,1)=(Vol_fcst_call(i,1)+Vol_fcst_put(i,1))/2;
        end
        [Hit_rate, HitNo]=hit_rate_ANN(IV_mdl_average(1:n,1), Vol_fcst_avg(1:n,1));

        % Annualized Return
        Ret_G=mean(GARCH_portfolioV(n,1)/GARCH_portfolioV(1,1))-1;
        Ret_m=(PortfolioV(n,1)/PortfolioV(1,1))-1;
        Ret_ann=((1+Ret_m)^(250/n))-1;
        Ret_GARCH=((1+Ret_G)^(250/n))-1;

        % Sharpe Rate for ANN and GARCH
        Rf=mean(r); % Find the corresponding rate from the vector of 4 weeks T-Bill
        Mean_retG=GARCH_Profit(1:n,1);
        Sharpe_Garch = sharpe(Mean_retG, Rf);

        Mean_ret=Profit(1:n,1);
        Sharpe_ANN = sharpe(Mean_ret, Rf);


%% 4. Diebold Mariano tests
% MSE validation- Diebold Mariano test, creating forecasting errors ME,
% calculate test statistics dm12,13,23 and group statistics to EMESE table

        l=length(Vol_fcst_avg_7);
        ME_ANN1=bsxfun(@minus,Vol_fcst_avg_7,IV_mdlaverage7);
        ME_ANN2=bsxfun(@minus,Vol_fcst_avg_8,IV_mdlaverage8);
        ME_ANN3=bsxfun(@minus,Vol_fcst_avg_9,IV_mdlaverage9);

        MSE_n_ANN1=ME_ANN1.^2;
        MSE_n_ANN2=ME_ANN2.^2;
        MSE_n_ANN3=ME_ANN3.^2;

        MSE_ANN1=sum(MSE_n_ANN1)/l;
        MSE_ANN2=sum(MSE_n_ANN2)/l;
        MSE_ANN3=sum(MSE_n_ANN3)/l;

        % Diebold_MAriano test: Computing test statistics
        dm12=dmtest(ME_ANN2, ME_ANN1, 1);
        dm23=dmtest(ME_ANN2, ME_ANN3, 1);
        dm13=dmtest(ME_ANN1, ME_ANN3, 1);
        EMESE=zeros(2,3);
        EMESEtbl(1,1)=MSE_ANN1; EMESEtbl(1,2)=MSE_ANN2;EMESEtbl(1,3)=MSE_ANN3;
        EMESEtbl(2,1)=dm12; EMESEtbl(2,2)=dm23;EMESEtbl(2,3)=dm13;
```